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ปีการศึกษา 2556

USING MULTI-DESCRIPTORS FOR REAL TIME COSMETIC IMAGE RETRIEVAL

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A Thesis Submitted in Partial Fulfillment of the Requirements

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เจนนิสา อารียาภินันท์ : การใช้ตัวบ่งชี้ลักษณะหลายประเภทสำหรับการค้นคืนภาพเครื่องสำอาง. (USING MULTI-DESCRIPTORS FOR REAL TIME COSMETIC IMAGE RETRIEVAL) อ. ที่ปรึกษาวิทยานิพนธ์หลัก: ผศ.ดร.พิษณุ คนองชัยยศ, อ. ที่ปรึกษาวิทยานิพนธ์ร่วม: ดร.อารัมภ์ กาวีวงศ์, 92 หน้า.

การค้นคืนภาพเครื่องสำอางเป็นกระบวนการค้นหาและค้นคืนภาพจากฐานข้อมูลภาพเครื่องสำอาง เนื่องจากเครื่องสำอางมีหลากหลายยี่ห้อและแต่ละยี่ห้อก็มีเครื่องสำอางหลากหลายประเภท รวมทั้งความซับซ้อนและหลากหลายของรูปร่างลักษณะและรายละเอียดของเครื่องสำอางต่างๆ ทำให้การค้นคืนภาพเครื่องสำอางทำได้ยาก ดังนั้นในงานวิจัยนี้จึงนำเสนอวิธีการค้นคืนภาพเครื่องสำอางโดยใช้ตัวบ่งชี้ลักษณะหลายประเภท ซึ่งจะทำการรวมตัวบ่งชี้ลักษณะโดยรวมเข้ากับตัวบ่งชี้ลักษณะเฉพาะส่วน ในงานวิจัยจะผนวกการเปลี่ยนรูปลักษณะสำคัญที่ไม่เปลี่ยนแปลงตามมาตราส่วน (ซิฟท์) เข้ากับตัวกรองจุดวิกฤต (ซีพีเอฟ) ซึ่งเรียกว่าซีพีเอฟเลเวล 9 และซิฟท์ เพื่อให้ได้การค้นคืนภาพเครื่องสำอางที่แม่นยำและรวดเร็ว โดยซิฟท์จะใช้กับภาพที่มีรายละเอียดมากๆอย่างเช่นภาพเครื่องสำอาง และเพื่อที่จะลดเวลาในการสกัดจุดสำคัญจากการใช้ซิฟท์ เราได้ใช้ซีพีเอฟซึ่งจะกรองเอาเฉพาะจุดวิกฤตของภาพ จากการทดลองพบว่างานวิจัยของเราสามารถลดเวลาในการประมวลผลได้ 50.46% จากซิฟท์และ 99.99% จากซีพีเอฟ อีกทั้งวิธีของเรายังสามารถรักษาความแม่นยำโดยวัดจากการทดสอบความแม่นยำและการเรียกคืนอีกด้วย โดยค่าเฉลี่ยการทดสอบความแม่นยำและการเรียกคืนของซีพีเอฟเลเวล 9 และซิฟท์จะมีค่าสูงใกล้เคียงกับซิฟท์

ภาควิชา วิศวกรรมคอมพิวเตอร์ ลายมือชื่อนิสิต ....

สาขาวิชา วิศวกรรมคอมพิวเตอร์ ลายมือชื่อ อ.ที่ปรึกษาวิทยานิพนธ์หลัก ....

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5570478721 : MAJOR COMPUTER ENGINEERING

KEYWORDs : IMAGE RETREIVAL / SCALE-INVARIANT FEATURE TRANSFORM / CRITICAL POINT FILTERS / COSMETIC

JENNISA AREEYAPINAN: USING MULTI-DESCRIPTORS FOR REAL TIME COSMETIC IMAGE RETRIEVAL. ADVISOR: ASST.PROF. PIZZANU KANONGCHAIYOS, Ph.D., CO-ADVISOR: ARAM KAWEWONG, Ph.D., 92 pp.

Cosmetic Image Retrieval (CIR) is a methodology for searching and retrieving images from Cosmetic Image Collection (CIC). There are numerous cosmetic brands whose types are similar to others. In addition, there are not trivial to retrieve cosmetic images because of its complexity and duplicative shape, as well as detail of various cosmetic items. We present a method for CIR using multi-descriptors, combining global and local features for image descriptors. Along with integrating a Scale-Invariant Feature Transform (SIFT) and Critical Point Filters (CPFs) to achieve accuracy and agility in CIR processing, called CPF level 9 & SIFT. SIFT is used for detailed-image, such as cosmetic image, to reduce the time complexity for extracting keypoints. On the other side, CPF will filter only for the critical pixel of the image. From the experiment, our method can reduce computation time by 50.46% and 99.99% by using SIFT and CPF respectively. Moreover, our method is preserved efficiency, measured by precision and recall of CPF level 9 & SIFT, which is as high as the precision and recall of SIFT.

Department: Computer Engineering Student’s Signature: ....

Field of Study: Computer Engineering Principal Advisor’s Signature: ....

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Contents

Page

Page

List of Tables

Page

List of Figures

Page

Page

Page

Page

CHAPTER I

Introduction

In this chapter, we mention about the problem and background of cosmetic image retrieval. Moreover, we also mention the gap of available techniques of this research.

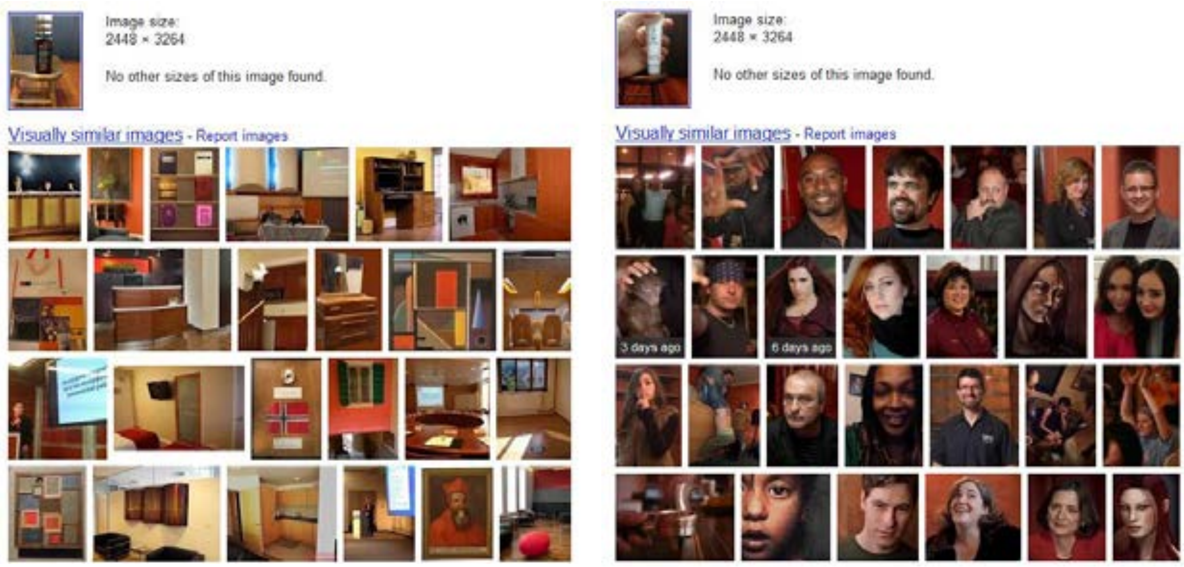
1.1. The Problem

There are a lot of cosmetics that have been produced for both women and men such as body lotion, eye cream and shampoo. Moreover, there are numerous cosmetic brands around the world such as Estee Lauder, NIVEA, Clinique and Bobbi Brown and each brand has a lot of in-brand itself which could be possible up to 20 to 50 items or more as shown in Figure 1. The shape of the cosmetics will also be similar to others in its brand or in other brands' product. Thus, this is the reason that cosmetic customers can get confused easily.

Figure 1. Example of Cosmetics.

Source of http://www.articlesweb.org.

Cosmetic image retrieval is a method of searching and retrieving cosmetic image from image collection. There are numerous of search engines; such as Google™ and Yahoo!®, that can retrieve image by using textual descriptors or by using image as an input. When we try to retrieve cosmetic images by using images as an input by Google™, we got the result as shown in Figure 2. According to Figure 2(a), we search a cosmetic image and then we get the images of rooms and furniture instead. Moreover, from Figure 2(b), we retrieved the images of human faces. Hence, we know that the retrieved image from Google™ has high probability that the result will not be cosmetic images at all.



(a) (b)

Figure 2. Cosmetic image Retrieval by using image as an input from Google™.

If we use textual descriptors to search cosmetic images from Google™, We have to input a lot of information details and keywords of cosmetic item as shown in Figure 3 to get the exact cosmetic images that is correct. Furthermore, the way we can retrieve the cosmetic image using textual descriptions via Google™, we need to know the details of that cosmetic product. If the product details are in other languages such as Chinese and Korean as shown in Figure 4, we cannot use textual descriptions to search images at all.

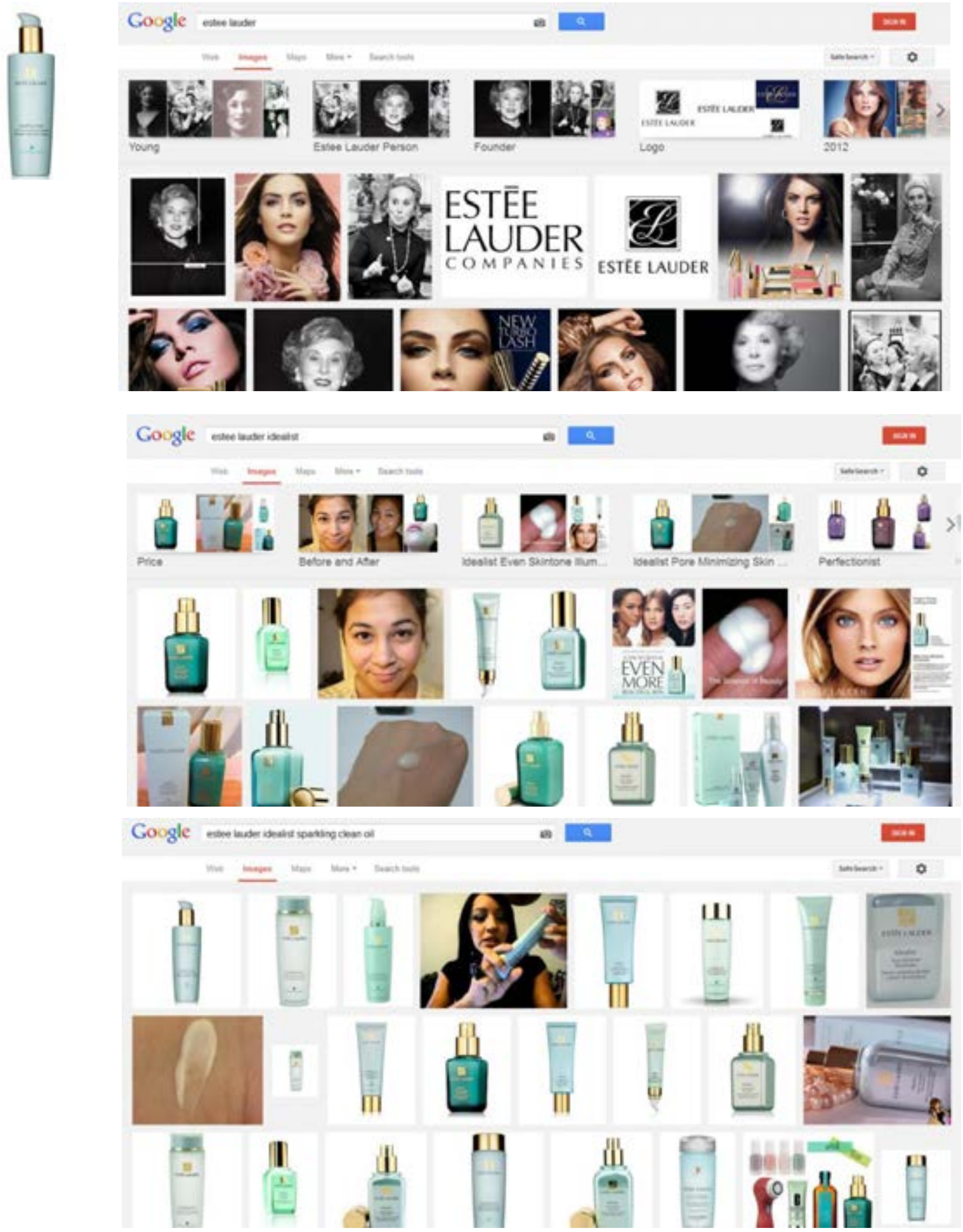


Figure 3. Cosmetic image Retrieval by textual description from GoogleTM, On the left side is the cosmetic image which will be retrieved, on the right side from top to bottom are added more keywords until getting the correct result.

Figure 4. Examples of cosmetic image in other languages.

Due to the troublesomeness of using textual descriptions in cosmetic image retrieval, content-based image retrieval (CBIR) is used to represent an image similarity from visual content instead [1]. However, there is still one open problem with CBIR, it is hard to achieve the satisfactory in evaluating the efficiency of visual similarity and semantic similarity.

However, there are various proposed solutions for image retrieval which is using descriptors to describe the details of image. For example, image segmentation, pyramid histogram of oriented gradient and critical point filters. All the solutions has the strong points and weak points which trade-off between speed and accuracy. Thus, our research will find how to combine various descriptors in cosmetic image retrieval for decreasing computing time while preserving accuracy.

1.2. Objective

To propose a framework for cosmetic image retrieval based upon CPF pyramid and SIFT.

1.3. Scope of the Research

The input image that would make this algorithm most effective must have some special qualities to get the result image that satisfied the users.

1.3.1. Input Image

The input image that would make this program most effective has to have some special qualities. That shows in Figure 5 is the image that will get satisfied result the users.

- frontal cosmetic image with only one cosmetic item
- image size $2^n \times 2^n$; n is countable number
- image taken from camera (the resolution is 2448x3264 pixels)

Figure 5. The example of the input images.

1.3.2. Output Image

The output image is the retrieved image from image collection. Output images are shown in Figure 6.

- frontal cosmetic image
- image with only one cosmetic item
- image size $2^n \times 2^n$; n is countable number

Figure 6. The example of the result images.

1.4. Problem Statement

According to the difficulty in cosmetic image retrieval using textual descriptions, the CBIR is used in retrieving cosmetic image instead. Thus, to rank the similarity between cosmetic images, we have to consider various mathematical descriptions of an image which will be called image signatures.

There are two methods for retrieving cosmetic image. The first is non-descriptor image signature and another is descriptor image signature.

First, non-descriptor image signature is textual descriptions. This is not usable in cosmetic image retrieval because cosmetic customers need to know the keywords for retrieving correct image from search engine image collection.

Second, CBIR, is a descriptor image signature, uses for retrieving cosmetic image. CBIR could extract the image signature from the image by using color, salient point, texture or other image features.

To rank the similarity between cosmetic images, we have to consider various image signatures. Thus, cosmetic customers do not need to know the keywords or details of the cosmetic that they want to retrieve. However, each image descriptor has its own strong points and weak points which will be mentioned in topic 2.1, hence; using multi-descriptors would help improving retrieval efficiency because different types of descriptor could support each other.

Hence, in our research, we provide real time cosmetic image retrieval system. Moreover, multi-descriptors have been adopted in our works to improve the accuracy and computation time.

1.5. Thesis Statement

Combining global and local features for image descriptors could decrease computing time while preserving accuracy for cosmetic image retrieval.

1.6. Evaluation

In our research, we design an algorithm for real time cosmetic image retrieval. To evaluate the efficiency, we would use precision and recall to measure the accuracy. Moreover, to evaluate the effectiveness, we would count computation time comparing among other image retrieval methods.

1.7. Expected Outcome

Expected outcome is the designed algorithm could perform the accurate and real time cosmetic image retrieval system on image collections.

1.8. Expected Benefit

Our research designs an algorithm for real time cosmetic image retrieval with accuracy. Our algorithm improves performance of cosmetic image retrieval which decreases computation time compare to previous algorithm and does not reduce accuracy.

1.9. Outline

In this research, we combine the CPF to extract cosmetic image features with SIFT to provide keypoint matching for enhancing the performance and matching speed. The combination of our method is using CPF to filter the critical points of cosmetic image and the CPF critical points can reduce the amount of interest points of SIFT. Chapter 2 provides a further review of image retrieval systems and CPF that will be applied together. Then chapter 3 shows the methodology of how to integrate CPF and SIFT for cosmetic image retrieval. The experimental results in chapter 4 show that the proposed method gives an improvement in cosmetic image retrieval method. Finally, in chapter 5, we also discuss and summarize our findings and future suggestions.

1.10. Research Publication

This research is published for a topic of " Using Multi-Descriptors for Khon Image Retrieval" in the International Conference on Culture and Computing (Culture and Computing 2013) which will be held from September 16^{th} to 18^{th} in Kyoto, Japan.

CHAPTER II

Related Works and Background

In this chapter, we review the algorithms which relate to our work. The CBIR algorithm can be divided into 4 groups. The efficiency and the effectiveness depend on how to describe an image by mathematical descriptor and how to evaluate the similarity between two images [1].

2.1. Literature Review

CBIR technology has been wildly used in real-world, numerous methods and techniques have been adopted to provide the powerful image retrieval system.

According to ACM computing surveys [1], extraction of visual signatures in image retrieval techniques have been divided into four major groups as shown in Figure 7.

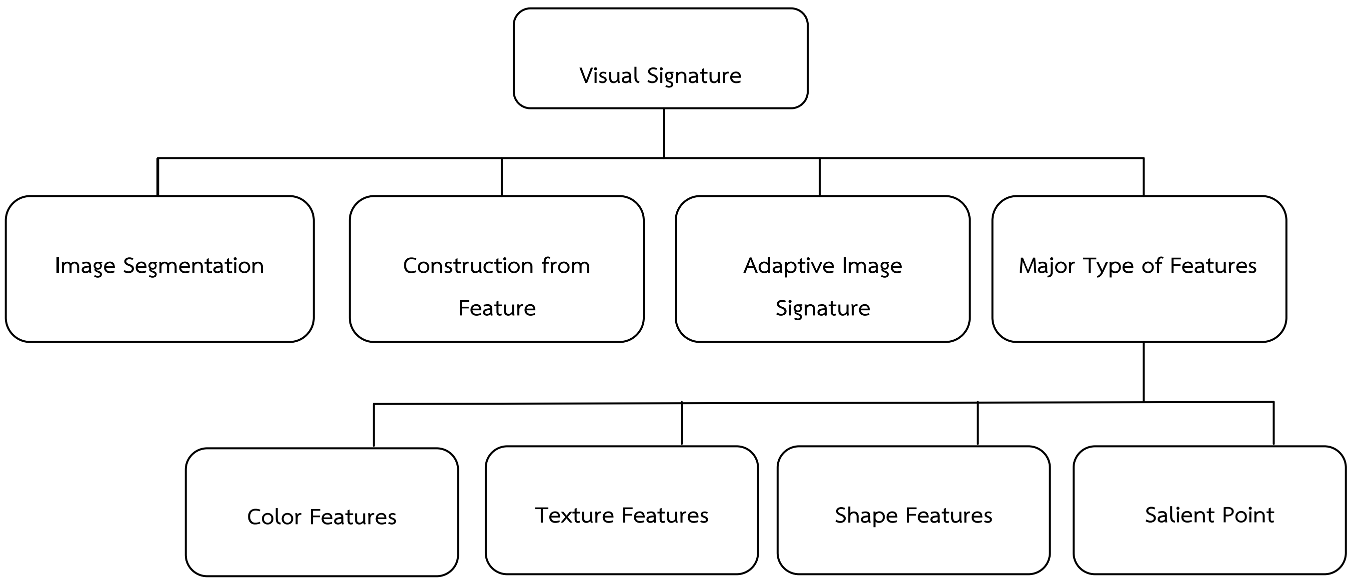


Figure 7. Diagram of Visual Signature divide following ACM computing surveys "Image Retrieval: Ideas, Influences, and Trends of the New Age " .

2.1.1. Image Segmentation

Image segmentation is to segment image based on k-means clustering and acquire region based descriptors. This method has been used in the very first image retrieving and developed into other image retrieval methods. Image segmentation is the most basic and fast in processing for cosmetic image retrieval. However, image segmentation can classify only shape of cosmetic but cannot classify type and brand of cosmetic as shown in Figure 8. The reason is that the cosmetic could have duplicate shape both in different brands and in the same brand. Thus, this method is not suited for applying in cosmetic image retrieval for all above reasons.

(a) Input Image (b) Segmented Image

Figure 8. An Example of Image Segmentation.

For example, the work of Wang et al. 2001 for multiresolution segmentation of low-depth-of-field images, and another work of Milik et al. 2001 for textured image segmentation by using cues of contour and texture differences [1]. Moreover, the work of Chen et al. 2005 for adaptive perceptual color-texture image segmentation [12].

2.1.2. Construction of Descriptors from Feature

To construct descriptors from feature is to describe the image feature in the form of vectors and distributions called histograms and region-based as shown in Figure 9. According to Hadjidemetriou et al., multiresolution histogram is an effective method in retrieving textured images. Moreover, histogram could also accurately detect some type of objects such as human [16].

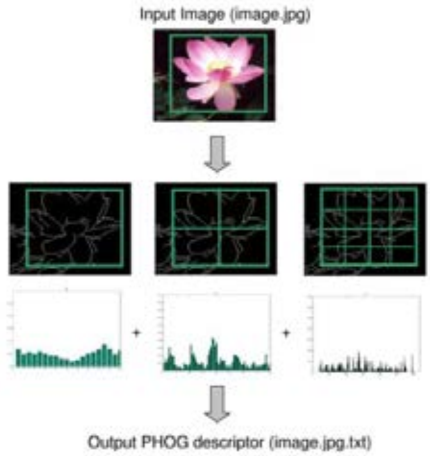


Figure 9. An Example of Pyramid Histogram of Oriented Gradients (PHOG).
Resource of http://www.robots.ox.ac.uk/~vgg/research/caltech/phog.html.

However, the disadvantage of histogram for cosmetic image retrieval is similar to the disadvantage of the shape feature in major type of feature above. That is it cannot extract the cosmetic brand name and type very well due to the similarity of shape in brand and type. According to Table 1, using histogram gives a good result because the shape of input cosmetic item is outstanding and different from the others. However, from Table 2, the result is not accurate because the shape of input cosmetic item in this table is similar to the shape of various cosmetic items in database. Thus, constructing descriptors from feature could loss some prominent characteristics of the cosmetic image.

Table 1. An example of Using Construction of Descriptors from Feature.

Input Image 	Result Image				
	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5
L=0					
L=1					
L=2					
L=3					

Table 2. An example of Using Construction of Descriptors from Feature.

Input Image 	Result Image				
	Rank 1	Rank 1	Rank 1	Rank 1	Rank 1
L=0					
L=1					
L=2					
L=3					

2.1.3. Adaptive Image Descriptor

Adaptive image descriptor is developed to improve the accuracy and reliable of image retrieval by tuning descriptors based on image and user feedback. After receiving user feedback, learning methods could help improving the efficiency of image retrieving process. Thus, adaptive image descriptor could help improving the performance in cosmetic image retrieval. For example, in context based object categorization [17] as shown in Figure 10, various sets of training images had to be trained for getting accurate results. This methods is relying on the training to get more accurate result and is suitable for the image collection that can divided into a few groups of image type. However, training process would spend time to achieve the goal of accuracy and cosmetic images can be divided into a lot of groups. Furthermore, there are not enough sample cosmetic images in our image collection to achieve the accurate result. Thus, this method is not suit to apply in cosmetic image retrieval.

Figure 10. An Example of Adaptive image descriptor.
Resource of Context based object categorization: A critical survey by C. Galleguillos et al.

2.1.4. Major Types of Features

Major types of features are the visual characteristic of image which can be divided into global features and local features. Global features are color features, texture features and shape features. Local feature is salient points [1].

In color features, the image would be divided into small sub-image and the computation of every pixel in sub-image would be computed using its neighbor pixels. Thus, to reduce computation, the sub-image should not be overlapping each other. Using only color feature in cosmetic image retrieval would not give the satisfactory result because cosmetic brand name cannot be classified by using only color feature.

According to Figure 11(a) and Figure 11(b), the color of each cosmetic item is similar to each others that using color feature cannot classify the brand and type of cosmetic correctly.

(a)

(b)

(c)

(d)

Figure 11. An example of cosmetic items which are similar in color, texture and shape.

Second, texture features are often used in the repeated form of surface of image such as fur of animal, field and grass in the lawn. However, this method is not suited for applying in cosmetic image retrieval because the texture of the cosmetic is very similar to each other as shown in Figure 11(a) - Figure 11(d).

Next major type is features of shape; this feature is one of the prominent features. Shape descriptor could match the shape similarity of a pair of images together. Hence, shape descriptor could be used to provide effective and reliable image retrieval. However, the limitation of shape descriptor in cosmetic image retrieval is that it is difficult to classify the difference between similar shapes of cosmetics. From Figure 11(d), the shape of each cosmetic item is very similar to each others that using shape feature cannot classify the correct cosmetic item.

The example work of color feature, texture feature and shape feature is the work of Wang et al. which could retrieve the image effectively [13] and Belongie et al. had proposed shape context for similarity matching which could eliminate noise and unimportant shape feature of image [1].

Last feature is salient point. This feature is based on local invariant feature. Salient point is the outstanding point of image. The strong point of local invariant feature is that scale, translation, rotation and illumination changes do not make the proficiency in cosmetic image retrieval decreased. Moreover, it can also classify brand and type of cosmetic by matching interest points together.

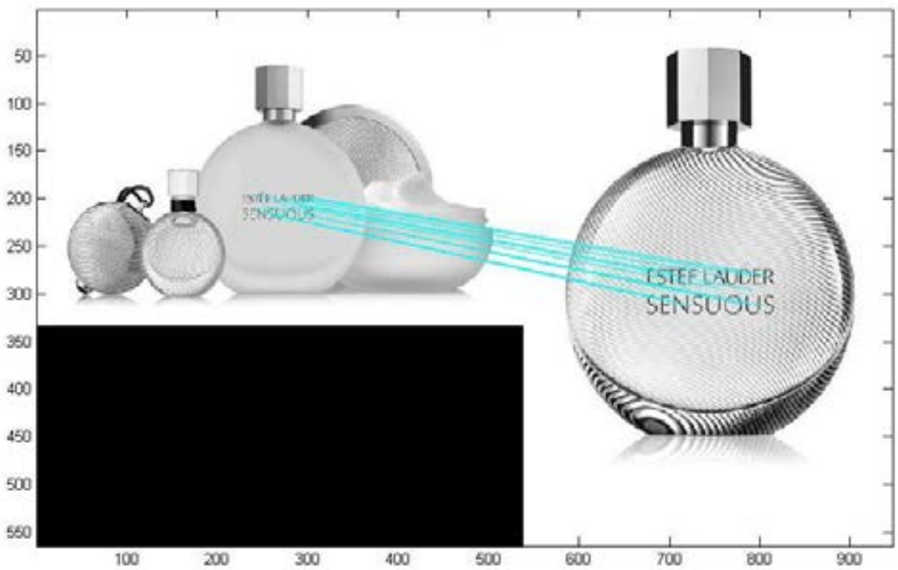


Figure 12. An Example of SIFT keypoint matching in cosmetic image.

For instance, from Figure 12, scale-invariant feature transform (SIFT) use image key to identify the candidate object matching between a pair of images [2,3,4]. Furthermore, speeded up robust feature (SURF) is very useful in robotic works which need fast processing time [14]. However, even SURF is faster than SIFT in computation, SURF is not as good as SIFT in accuracy and rotation [15].

2.1.5. Conclusion

In conclusion, image segmentation, major type of color feature, major type of shape and histogram are not suited for applying in cosmetic image retrieval because the difficulty in brand and type classification. Moreover, using only texture feature is also not suited because texture cannot classify brand and type of cosmetic at all and adaptive image descriptor is not facilitate for the user. From mentioned above, we will find that using only one type of major type of feature cannot retrieve the exact cosmetic images. Thus, in our research, we will combine four major types of feature together. We will represent global feature which consist of color feature, texture feature and shape feature by critical point filters (CPFs) [5,6,7,8,9,10,11] and local feature which is salient point by scale invariant feature transform (SIFT).

2.2. Theory

From mentioned above, in this research, we will uses two types of descriptors which are local feature and global feature. Those are scale invariant feature transform and critical point filters.

2.2.1. Scale Invariant Feature Transform (SIFT)

Scale Invariant Feature Transform (SIFT) is an algorithm that can provide image retrieval that scale, translation, rotation and illumination changes do not make the performance decreased. Thus, we apply SIFT as local feature in our research.

There are four major steps to providing SIFT descriptor [2,3,4]. First, scale-space extrema detection is using a difference-of-Gaussian function to obtain the interest points of all scale and location of image. Then, find location of SIFT keypoint by considering the stability among candidate location. Next, assign orientation to SIFT keypoint from the previous step. Each keypoint can have more than one orientation up to gradient direction. Finally, each keypoint is computed to obtain local keypoint descriptor by using image gradient.

2.2.1.1. Detection of Scale-Space Extrema

First, using Gaussian function, which know as a continuous function of scale or scale space, to identify the location and scale of keypoint. Then, compute for difference-of-Gaussian function.

According to Figure 13, to compute difference-of-Gaussian (DoG), initial image would convolve with Gaussian to produce octaves of scale space. Then, the adjacent Gaussian images on the left side would be subtracted to obtain the difference-of-Gaussian on the right side. This process would be repeatedly provided in every octave of scale space.

The strong point of using difference-of-Gaussian function is that it is a powerful function to compute in any case of scale space feature description. Furthermore, this function could produce the close estimate value to the scale-normalized Laplacian of Gaussian.

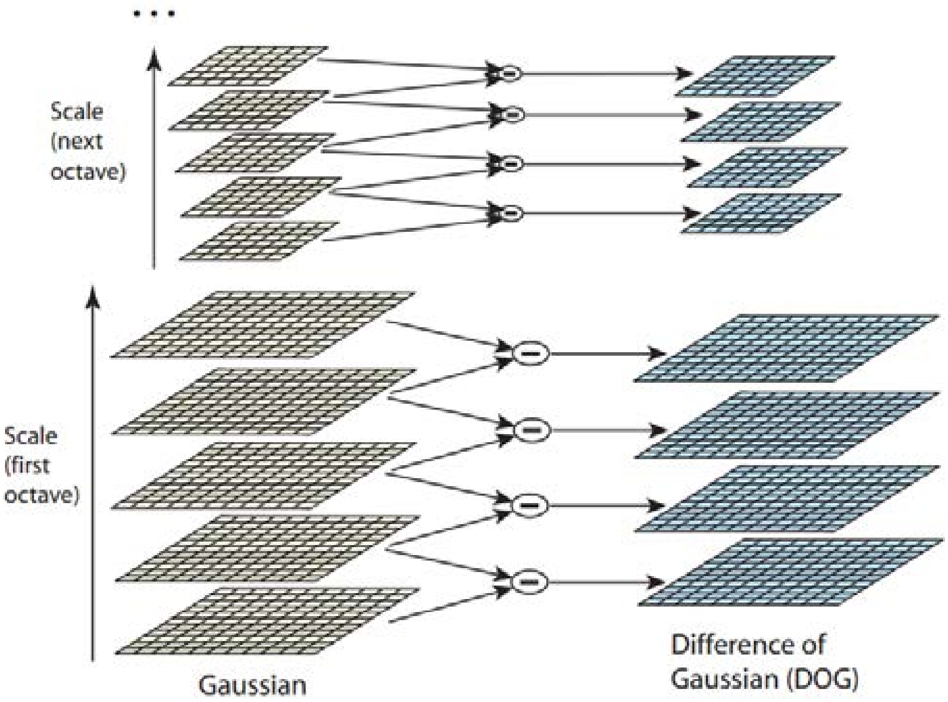


Figure 13. The Difference-of-Gaussian Computation.
Resource of Distinctive Image Features from Scale-Invariant Keypoints by Lowe.

Next, detecting local extrema by considering each sample point which would be selected only when it is the largest or the smallest among its neighbors. If the sample point is the largest point, it is called the local maxima. However, if it is the smallest point, it will be called the local minima as shown in Figure 14.

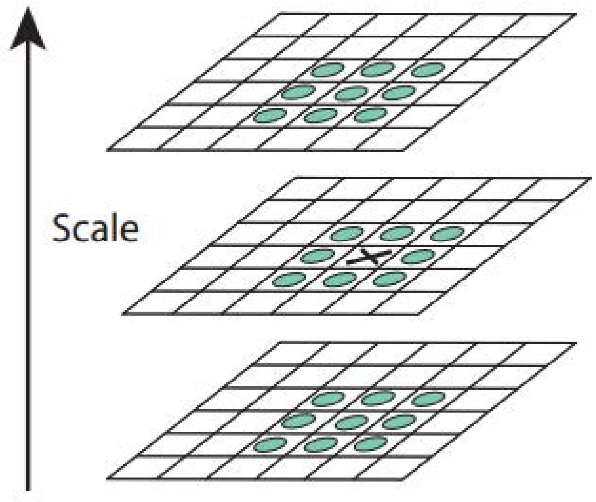


Figure 14. The Maxima and minima of the Difference-of Gaussian.
Resource of Distinctive Image Features from Scale-Invariant Keypoints by Lowe.

2.2.1.2. Keypoint Localization

After detecting scale space extrema, we would determine the accurate position for each candidate keypoint by interpolating nearby data. The quadratic Taylor expansion of the difference-of-Gaussian scale-space function would be used to get the interpolation. Then, low-contrast keypoint and noise sensitive keypoint would be eliminated by the Hessian and derivative of D function value at extremum as in Figure 15. Last, eliminate the edge response for stability because the difference-of-Gaussian would have high edge response.

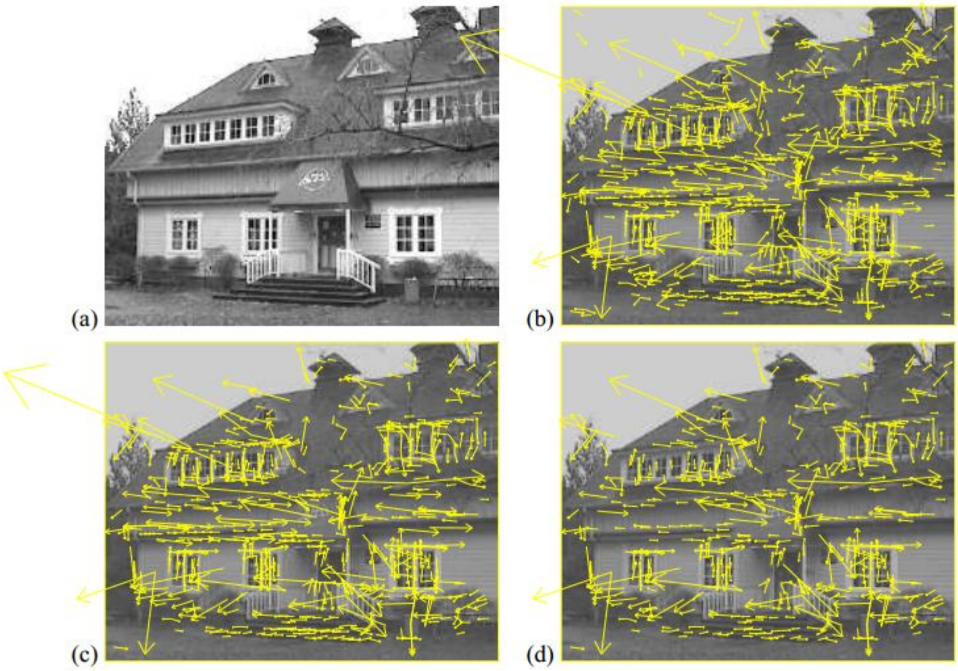


Figure 15. The Example of keypoint selection. (a)Original Image. (b) The initial 832 keypoints locations. (c) 729 keypoints left after defining initial minimum contrast. (d) Final 536 keypoints left after defining the initial ratio of principle curvatures.

Resource of Distinctive Image Features from Scale-Invariant Keypoints by Lowe.

2.2.1.3. Orientation Assignment

In this step, the keypoint, which would be assigned one or more orientations based on local image gradient directions, is invariant to image rotation. Using scale of the keypoint for choosing the Gaussian smoothed image which would make the scale-invariant computation.

2.2.1.4. Keypoint Descriptor

According to Figure 16, compute keypoint descriptor vector for each keypoint by performing image closest in scale to the scale of keypoint. After this step, keypoint would be highly distinctive and invariant.

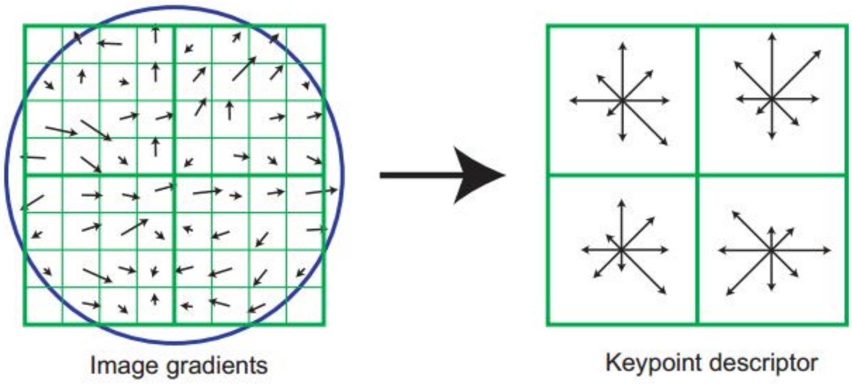


Figure 16. The figure shows a keypoint descriptor computation.
Resource of Distinctive Image Features from Scale-Invariant Keypoints by Lowe.

We apply SIFT for cosmetic image retrieval because SIFT can classify cosmetic image both brand and in-brand with accuracy. However, fine cosmetic image give more accurate result but use more computation time than coarse cosmetic image. Thus, we will improve this weak point by combine critical point filters (CPFs) with SIFT to reduce interest point in SIFT method which we will explain in chapter 3.

2.2.2. Critical Point Filters (CPFs)

From mentioned above, we use SIFT to classify brand and in-brand of cosmetic image. However, using only SIFT in the cosmetic image retrieval will spend a lot of processing time. Thus, to develop our method, we adopt CPFs; as global feature consists of color feature, texture feature and shape feature, to decrease computation time. The reason is that CPF can filter the prominent points of cosmetic image which can be extracted interest points for SIFT and reduce the amount of interest points which will help decrease computation time in next process.

Critical Point Filters method is a method that could extract the main features of the images by dividing the color of the images into four groups of images [5,6,7,8,9,10,11].

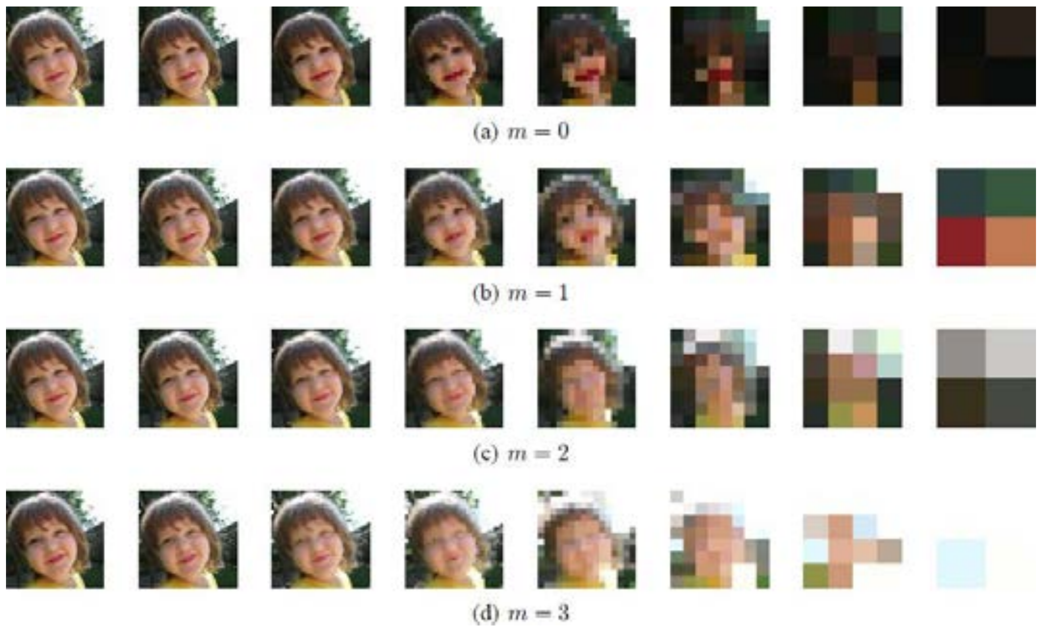


Figure 17. Four Groups of Image after Passing the Critical Point Filters.
Source of Point- and Window-Based Matching in Images Using Critical-Point Filters by B.J. Chambers

According to Figure 17, input images would be divided into four groups and m is the type of the groups. From Table 3, type number 0 refers to the maximum sub-image, type number 1 refers to the max-min saddle sub-images, type number 2 refers to the min-max saddle sub-image and type number 3 refers to the minimum sub-image. The maximum sub-image extracts the maximum color of the input image which could be eyes and hair. The max-min saddle sub-image extracts the max-min color of the input image which could be lip, T-shirt and the leaves of the tree in the background. The min-max saddle sub-image extracts the min-max color which could be the skin and last is the minimum sub-image extracts the minimum color of the input image which could be the sky in the background.

Type Number	Type Name
0	Maximum sub-image
1	Max-min sub-image
2	Min-max sub-image
3	Minimum sub-image

Table 3. The four groups of sub-images table.

After passing input image through the critical point filters, the result would be the image pyramid. The image pyramid shows in Figure 18.

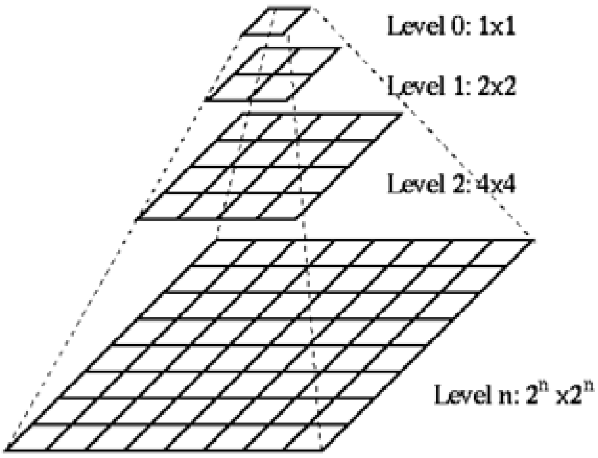


Figure 18. Image Pyramid Hierarchy.

The lower hierarchy is a child and the higher hierarchy is a parent. Each child hierarchy is finer and two times bigger than their parent as shown in equation (1).

$$parent(i,j) = \left(\left\lfloor\frac{i}{2}\right\rfloor, \left\lfloor\frac{j}{2}\right\rfloor\right) \tag{1}$$

The image hierarchies should be divided into 4 groups of sub-images by these four equations below (2) - (5). The source image and destination image would be $2^n x 2^n$ which n is countable number and m is hierarchy's number as in Figure 17 and Figure 19.

$p_{(i,j)}^{(m,0)}=min\left(\min\left(p_{(2i,2j)}^{(m+1,0)},p_{(2i,2j+1)}^{(m+1,0)}\right),\min\left(p_{(2i+1,2j)}^{(m+1,0)},p_{(2i+1,2j+1)}^{(m+1,0)}\right)\right)$ Minimum sub-image (2)

$p_{(i,j)}^{(m,1)}=max\left(\min\left(p_{(2i,2j)}^{(m+1,1)},p_{(2i,2j+1)}^{(m+1,1)}\right),\min\left(p_{(2i+1,2j)}^{(m+1,1)},p_{(2i+1,2j+1)}^{(m+1,1)}\right)\right)$ Saddle Min-Max sub-image (3)

$p_{(i,j)}^{(m,2)}=min\left(\max\left(p_{(2i,2j)}^{(m+1,2)},p_{(2i,2j+1)}^{(m+1,2)}\right),\max\left(p_{(2i+1,2j)}^{(m+1,2)},p_{(2i+1,2j+1)}^{(m+1,2)}\right)\right)$ Saddle Max-Min sub-image (4)

$p_{(i,j)}^{(m,3)}=max\left(\max\left(p_{(2i,2j)}^{(m+1,3)},p_{(2i,2j+1)}^{(m+1,3)}\right),\max\left(p_{(2i+1,2j)}^{(m+1,3)},p_{(2i+1,2j+1)}^{(m+1,3)}\right)\right)$ Maximum sub-image (5)

Where $p_{(i,j)}^{(m,0)}=p_{(i,j)}^{(m,1)}=p_{(i,j)}^{(m,2)}=p_{(i,j)}^{(m,3)}=p_{(i,j)}$ and $(0 \ll m \ll n)$

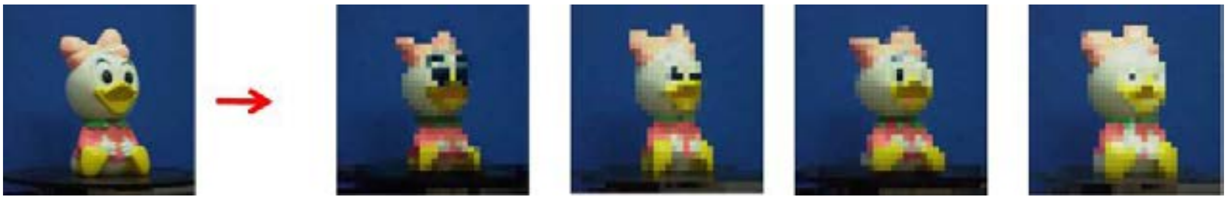


Figure 19. Example of 4 typed sub-images from left to right are input image, maximum sub-image, max-min sub-image, min-max sub-image and minimum sub-image.
Source of Image Interpolation Using Enhanced Multiresolution Critical-Point Filters by K. Hakuba and Y. Shinagawa.

CHAPTER III

Methodology

In our research, we would use two descriptors to design an algorithm for real time cosmetic image. The first descriptor is Scale Invariant Feature Transform (SIFT) which could extract the descriptor feature without disturbing by scaling, translation, rotation, illumination change or 3D projection. Moreover, Critical Point Filters (CPFs) would be used as other descriptors which could help reducing the amount of keypoints.

First, we explain what is brand and in-brand (type) of cosmetic image which will be used in the method and experiment step. Brand is the symbol of one cosmetic brand name which consists of brand name or logo or both as shown in Figure 20.

Figure 20. Example of Brand (Brand name and logo).

After classifying the brand, then we classify in-brand to find the exact cosmetic item. In each brand will have various products which will be called in-brand or type. In-brand or type of cosmetic is the information and details which helps us retrieve the exact cosmetic item correctly as shown in Table 4.

Table 4. Example of In-Brand or type of cosmetic items in one brand.

Brand	In-Brand (Type)
雪肌精 SEKKISEI KOSÉ	
NIVEA	
L'ORÉAL PARiS	
THE BODY SHOP®	
ESTĒE LAUDER	

According to Figure 21, a diagram shows the steps of cosmetic image retrieval. In this diagram, we divide the matching method into brand classification and type classification. First, we will find brand of cosmetic by using brand classification. After getting the brand already, we provide the in-brand (type) classification by using type classification to find the product in that brand which will retrieve the exact cosmetic item in one brand as shown in Figure 23.

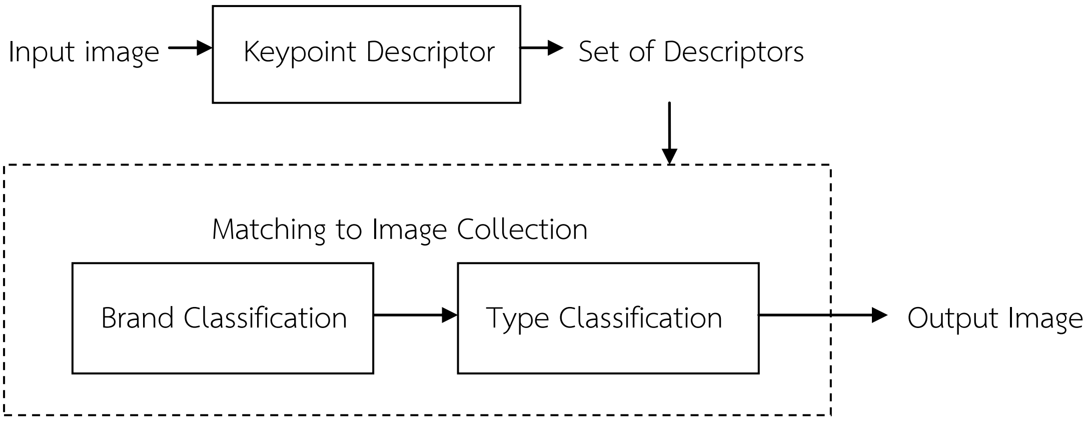


Figure 21. A Diagram of Cosmetic image Retrieval Method.

Moreover, Figure 22 shows the step of keypoint descriptor. In this diagram, we will find the keypoint descriptor by using David Lowe's SIFT keypoint detector. However, in the step of detecting scale-space extrema to get interest points, we will use CPF to filter the prominent point to reduce the amount of interest points in this step.

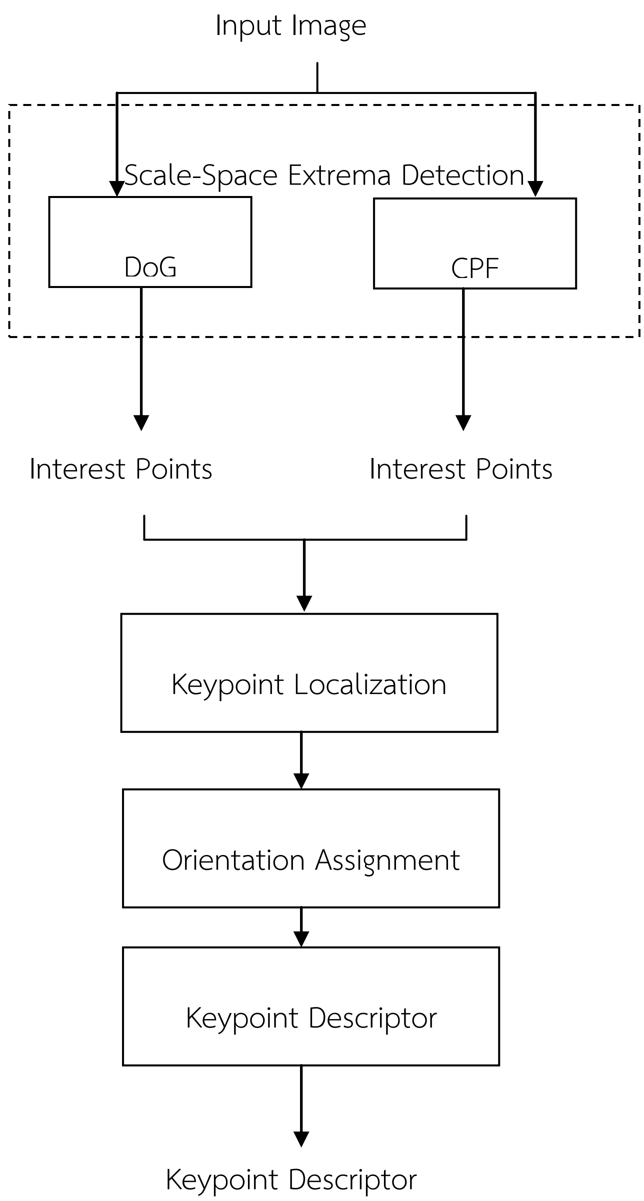


Figure 22. A Diagram of Keypoint Drescriptor Method.

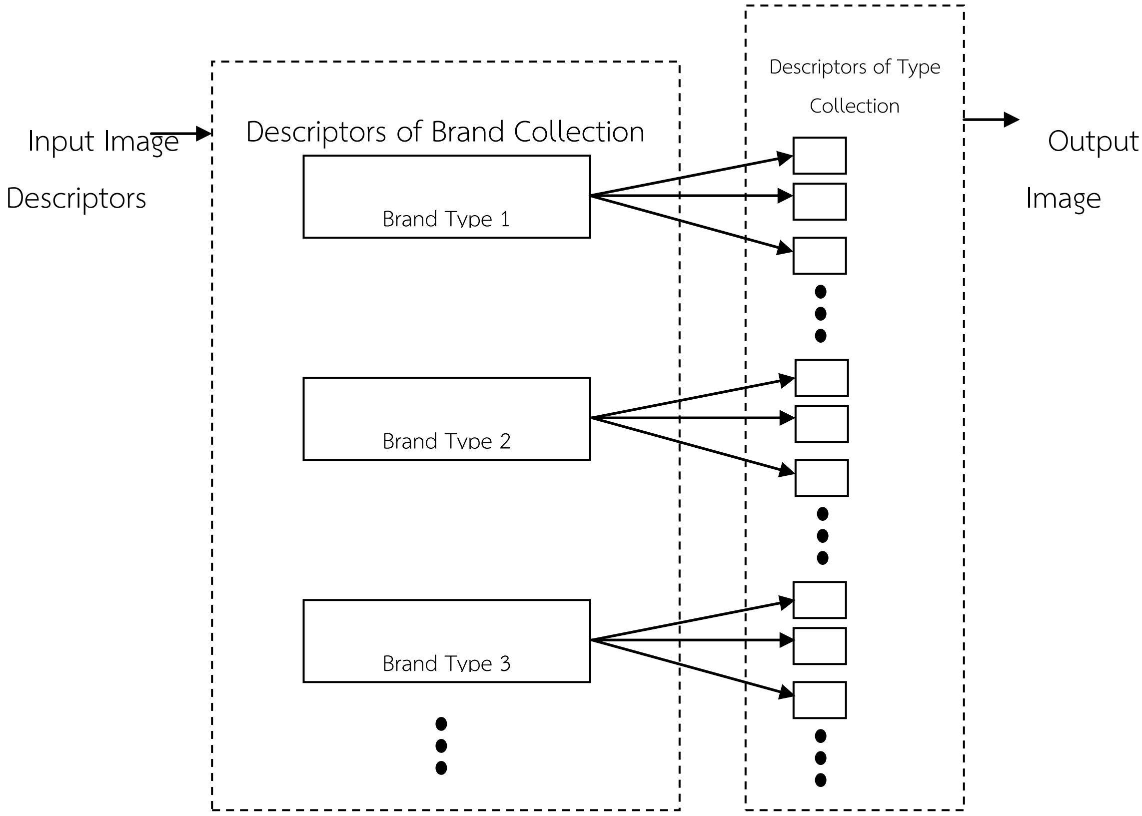


Figure 23. A Diagram of Image Collection.

In this research, we apply David Lowe's SIFT Keypoint detector and CPF to provide cosmetic image retrieval. As we mentioned above, using SIFT and CPF can improve cosmetic image retrieval to be highly accurate and reduce computation time. However, we have to preprocess the input cosmetic image because in order to provide image pyramid hierarchy the input image must have $2^n x2^n$ pixels. Furthermore, the higher level of image pyramid can be provided faster than the lower level of image pyramid but lacks accuracy. Thus, the most suitable CPF hierarchy level of image pyramid which when applied with SIFT produces a fast and accurate result will be determined in the experiment. The method can be categorized into three major steps.

3.1. Extract Interest Points

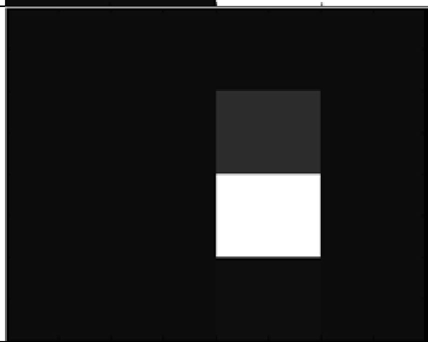
In this step, we divide the method into 3 parts as follows. To combine CPF and SIFT, we find CPF critical points of cosmetic image by using image pyramid hierarchy and find SIFT interest points. Then, we use CPF critical points and SIFT interest points to find the duplicate interest points which can help decreasing processing time in next steps of keypoint descriptor detection.

3.1.1. Hierarchies of Critical Point Filters

Critical point filter (CPF) can filter image by extracting critical point or prominent feature and create an image pyramid as shown in Table 5. However, the size of image in each hierarchy must be NxN = MxM $=2^n x 2^n$ pixels. We provide CPF with cosmetic image because CPF can filter prominent points of cosmetic image which do not reduce the performance of SIFT. Moreover, CPF filters cosmetic image to higher level of pyramid hierarchy which can reduce computation time in SIFT method. Thus, we use 512x512 pixels cosmetic image as input image as shown in Figure 24.

Figure 24. 512x512 pixels of Input Cosmetic Image.

Table 5. Images from Different Hierarchy of Image Pyramid.

CPF Level	Image Size	Cosmetic Image
0	1x1	
1	2x2	
2	4x4	
3	8x8	
4	16x16	

CPF Level	Image Size	Cosmetic Image
5	32x32	
6	64x64	
7	128x128	
8	256x256	
9	512x512	

3.1.2. Scale-Space Extrema

After filtering cosmetic image with CPF, we will get the higher hierarchy of cosmetic image that will decrease the amount of interest points in this step. In this step, we compute the difference-of-Gaussian (DoG) from input image. Then, we extract SIFT interest points by detecting local extrema.

3.2. Keypoint Descriptor Detection

According to Figure 22, a diagram shows the step of keypoint detection method. First, after input image, scale space extrema detection is performed to determine interest points from the previous step. Next, in keypoint localization, we would use the consistent points from SIFT's interest points and CPF's interest points to decrease the amount of keypoints. Then, assign the orientation and provide keypoint descriptors.

3.2.1. Keypoint Localization

The next step is determining the location for each candidate keypoint. We interpolate nearby data to get the accurate position by using quadratic Taylor expansion of DoG scale-space function.

3.2.2. Orientation Assignment

To assign orientation to keypoint, we use local image gradient directions. For one keypoint, we can assign one or more orientations.

3.2.3. Keypoint Descriptor

Next is the step of computing keypoint descriptor. In this step, we provide image closest in scale to the scale of keypoint to obtain each keypoint descriptor vector. This keypoint descriptor vector is invariant and highly distinctive.

3.3. Keypoint Matching

In matching process in Figure 21, the classification has been divided into brand classification and type classification because different type item images with the same brand name will be matched to input image. Thus, in brand classification, keypoints of input image would match to keypoint of cosmetic brand name in image collection. Then keypoints of brand name would be deleted from keypoints of input image, hence; we could match the remaining keypoints among the keypoint images with the same brand name correctly. Next, retrieve keypoints of all cosmetics in that brand from image collection and perform type classification by matching the remained keypoints with retrieved keypoints from image collection as shown in Figure 23.

CHAPTER IV

Experiment and Discussion

In this section, we describe the experiment of our algorithm and explain the result. We also analysis and discuss about the experimental results.

4.1. Tools for Experimentation

We use MATLAB for implementing the algorithms of brand classification and type classification in our research and also counting computation time. For taking cosmetic images, we use a digital camera with the resolution of 2448x3264 pixels.

4.2. Experimental Steps

The experiment is followed the steps as shown in Figure 25. The expected outcome and details of experiment are mentioned below.

According to Table 9, there are 100 images in image collection and 60 images as number of query. The image collection is divided into 5 brand types and each brand type has 20 images

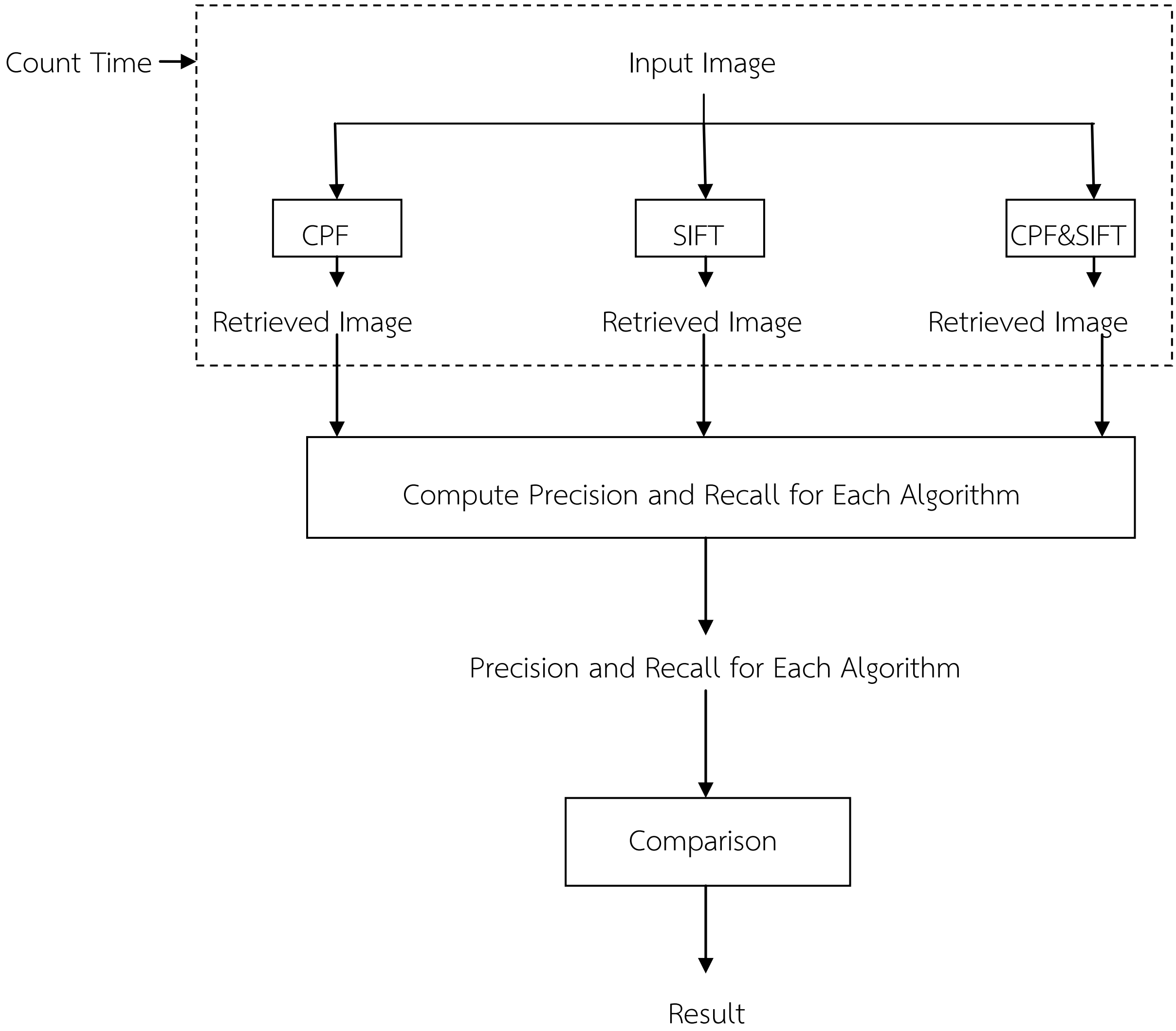


Figure 25. The Experimental Steps.

The details of the experiment steps will be divided into three topics. As describing below are performing each algorithm, compute precision and recall and comparison.

4.2.1. Performing Each Algorithm

In our research, we will perform 3 algorithms which are CPF, SIFT and CPF&SIFT. Then, we compare computation time and result of these 3 algorithms.

All 3 algorithms will follow the same steps. We would use the set of training image for extracting the keypoint descriptors of the cosmetic image in image collection. First step is extracting keypoint descriptors of brand and logo of cosmetic to obtain the set of brand and logo's descriptors. Next step is deleting the brand and logo's keypoint descriptors from each cosmetic image so that to obtain the type descriptors which will be remained.

4.2.2. Compute Precision and Recall

According to Figure 25, after obtaining the retrieved images from each algorithm, we compute precision and recall as in equation (6)-(8). We would measure the performance by using precision and recall and then compute for mean average precision (MAP) [18]. Precision is the fraction of retrieved images that are relevant to the search as shown in equation (6) and recall is the fraction of the documents that are relevant to the query that are successfully retrieved as shown in equation (7).

$$precision = \frac{|R_A|}{|A|} \tag{6}$$

$|R_A|$ is the number of retrieved images that are relevant to the search

$|A|$ is the number of retrieved images

$$recall = \frac{|R_A|}{|R|} \tag{7}$$

$|R_A|$ is the number of retrieved images that are relevant to the search

$|R|$ is the number of relevant images

$$MAP = \frac{\sum_{q=1}^{Q} AveP(q)}{Q} \tag{8}$$

MAP is the mean average precision

$AveP(q)$ is the average precision of at q^{th} retrieval

Q is the number of retrieval

4.2.3. Comparison

From previous step, we obtain precision and recall from CPF, SIFT and CPF&SIFT. Then, we compare them to measure the efficiency of each algorithm.

Moreover, we also use computation time of CPF, SIFT and CPF&SIFT. Comparing computation time can measure the effectiveness of each algorithm.

4.3. Experimental Result

The experimental result is shown in 3 topics: varying the hierarchy in the cosmetic image pyramid, matching the cosmetic image to the cosmetic image database, and matching small part cutting of image.

4.3.1. Varying Hierarchy in Cosmetic Image Pyramid

We find the matching points of cosmetic images at different hierarchies of the image pyramid. We use CPF to obtain the image pyramid and then use SIFT to find the matching points as shown in Table 6 by using input image as shown in Figure 26.

Figure 26. Example of Cosmetic Images Matching at Different Hierarchy.

Table 6. Example Result of Cosmetic Images at Different Hierarchy.

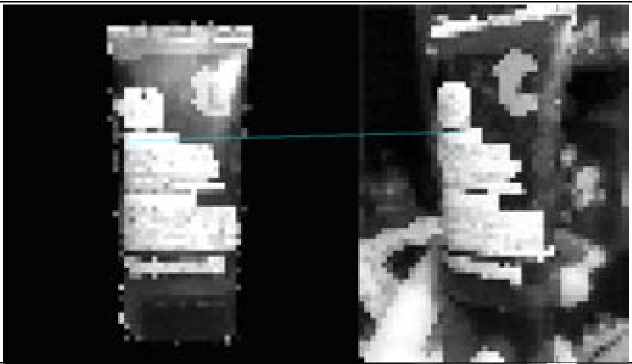
Level of Hierarchy	Image Size	Result Image
7	128x128	
8	256x256	
9	512x512	
10	1024x1024	

Table 7. Result of Cosmetic Images at Different Hierarchy.

Level of Hierarchy	Result			
	Average Time (s)	*Average Time Increase/Decrease (%)*	*Average Matching Points (points)*	*Average Matching Points Increase (%)*
6	0.059	-	5.83	-
7	0.070	18.6	25.2	332
8	0.082	17.1	46.5	84.5
9	0.101	23.2	187	302
10	0.219	116.8	349	86.6

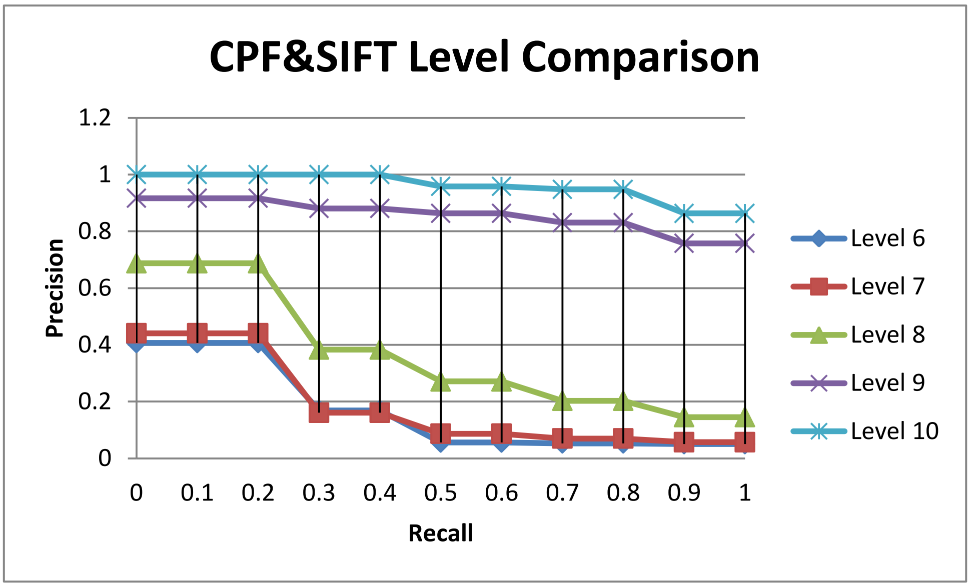


Figure 27. Precision and Recall Diagram of Each CPF&SIFT Level Comparison.

We start the experiment of image pyramid hierarchy at level 6 because the lower level is too small for SIFT to provide the octave of scale-space. According to Table 6, Table 7 and Figure 27, the best result is the image pyramid hierarchy at level 9. The result at level 9 is slower processing but more accurate compared to the result at hierarchy level 8 and below. However, although the precision and recall in hierarchy level 10 is the highest, the computation time is increased from hierarchy level 9 by about 116.8% which is very slow indeed. Thus, we choose to use the CPF at level 9 of the image pyramid hierarchy for the cosmetic image retrieval in our next experiment.

4.3.2. Matching the Cosmetic Image to Database

We categorize this section into 2 sections as brand classification and type classification. Our method starts with brand classification and then provides type classification.

From observing cosmetic brand, we can classify cosmetic brand into 5 main types. We will use 5 brand types of cosmetic in our experiment which can get the result for overall experiment cases as shown in Table 8 and Figure 28.

Table 8. The Details of Each Brand Type.

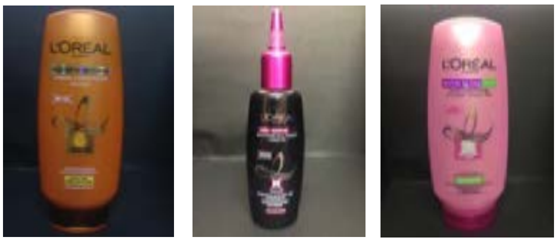
Brand Type	Brand Name	Logo	In-Brand Information	Shape & Color
Type 1	Big	None	Small	Similar
Type 2	Medium	Medium	Outstanding	Similar
Type 3	Medium	Outstanding	Medium	Different
Type 4	None	Small	Outstanding	Similar
Type 5	Big	Big	Outstanding	Different

(a)

(b)

(c)

(d)



(e)

Figure 28. Example for Each Brand Type. (a)Brand Type 1. (b) Brand Type 2. (c) Brand Type 3. (d) Brand Type 4. (e) Brand Type 5.

In image collection, there are 100 images which are divided into 5 brand types and each brand type has 20 images. All the images in image collection have black background as shown in Table 9.

From Table 10, test set can be divided into 3 test sets. Each test set has all the cosmetic items in the image collection. Test set 1 contains the cosmetic images with room background. Test set 2 is the cosmetic image which has a hand holding the cosmetic items. Last is test set 3, this test set has more illumination than test set 1 and test set 2.

Table 9. Cosmetic Images Collection.

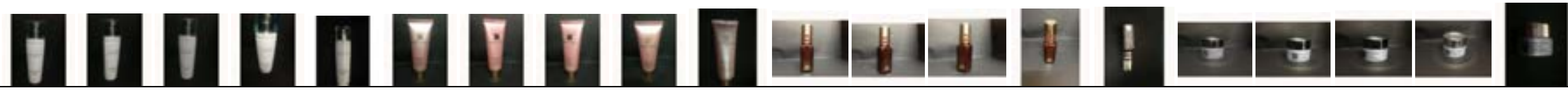
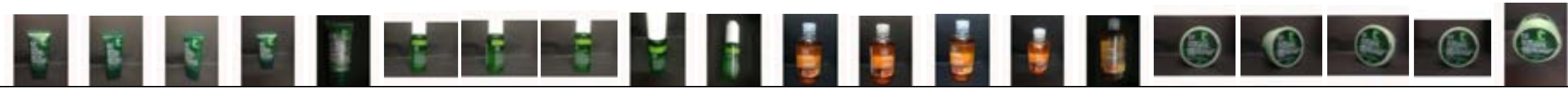
Brand Name	Images
Type 1	
Type 2	
Type 3	
Type 4	
Type 5	

Table 10. Test Set Cosmetic Images.

Test Set	Images
1	
2	
3	

4.3.2.1. Experiment of Brand Type and Test Set

We categorize the cosmetic database into 5 classes by brand of cosmetic items and each brand divided into 5 classes by type of cosmetic items, for which the size of all the cosmetic images is 512x512. Our method is performed and the efficiency is shown in Figure 29-40.

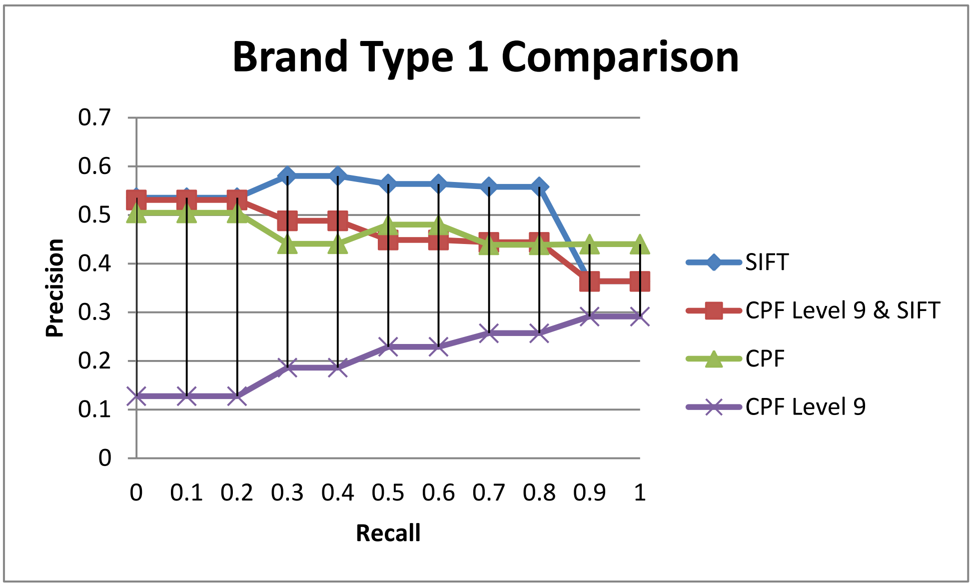


Figure 29. Precision and Recall Diagram of Brand Type 1 Classification.

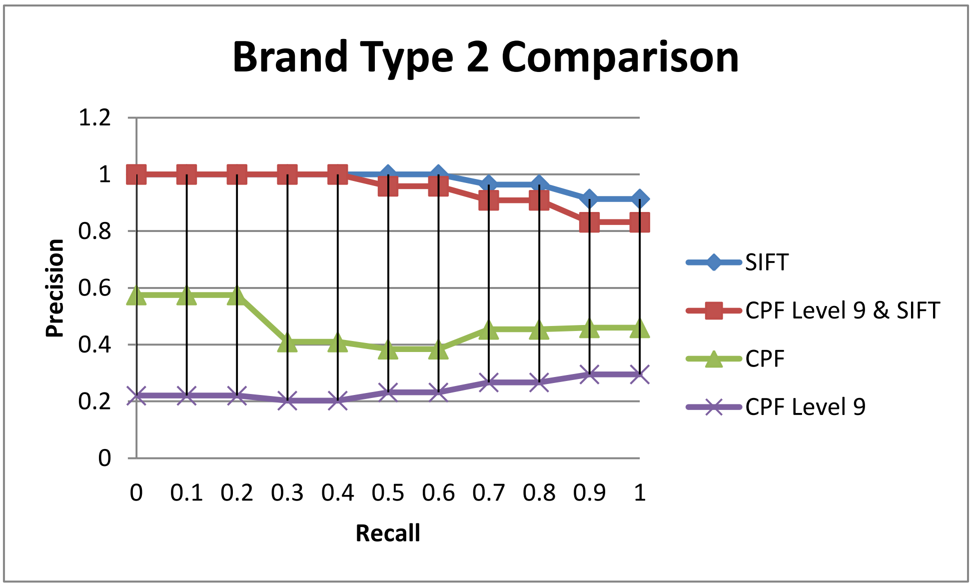


Figure 30. Precision and Recall Diagram of Brand Type 2 Classification.

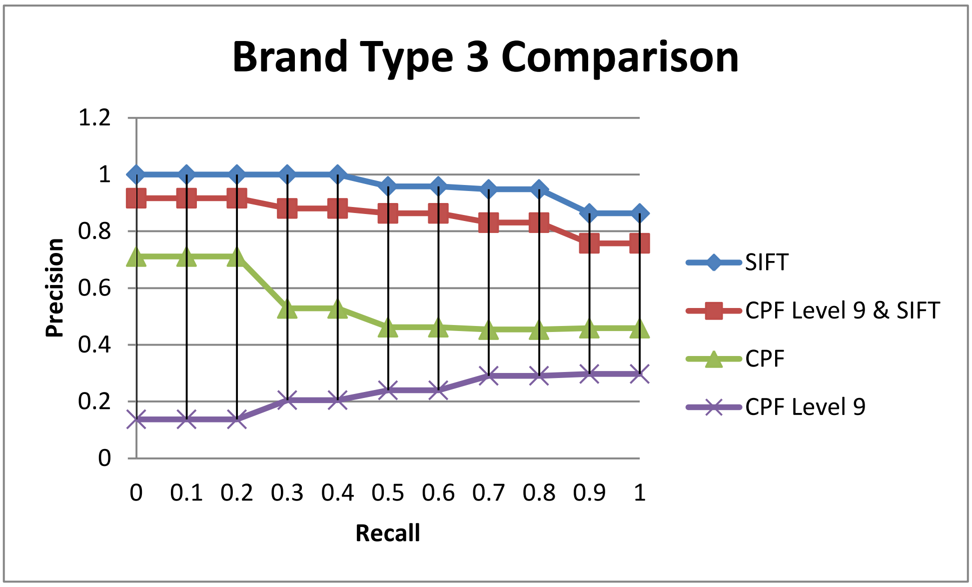


Figure 31. Precision and Recall Diagram of Brand Type 3 Classification.

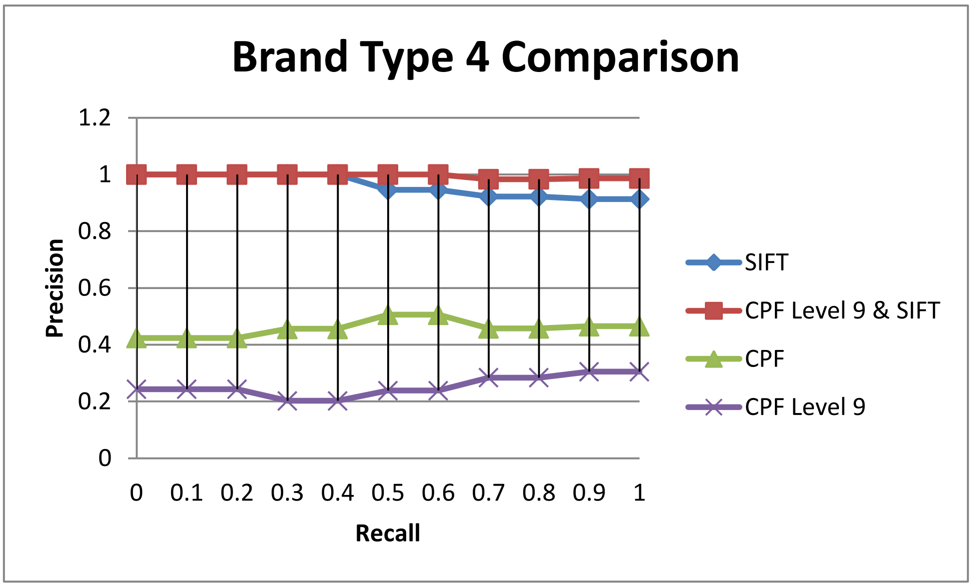


Figure 32. Precision and Recall Diagram of Brand Type 4 Classification.

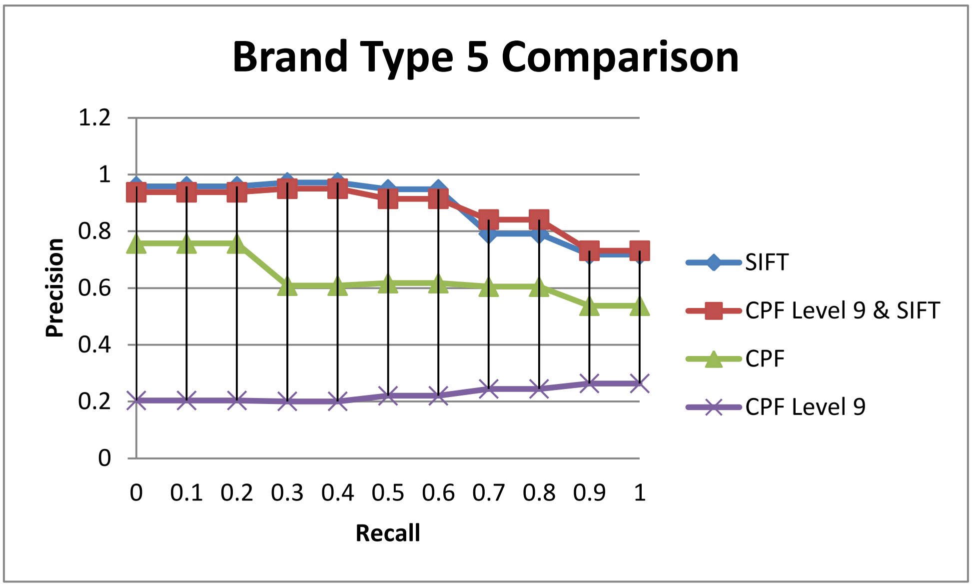


Figure 33. Precision and Recall Diagram of Brand Type 5 Classification.

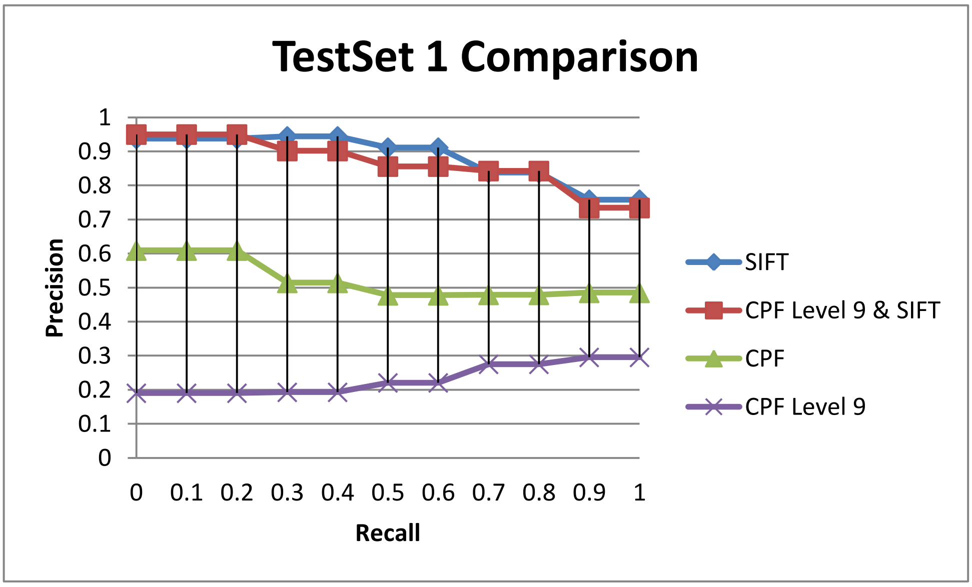


Figure 34. Precision and Recall Diagram of Test Set 1 Comparison.

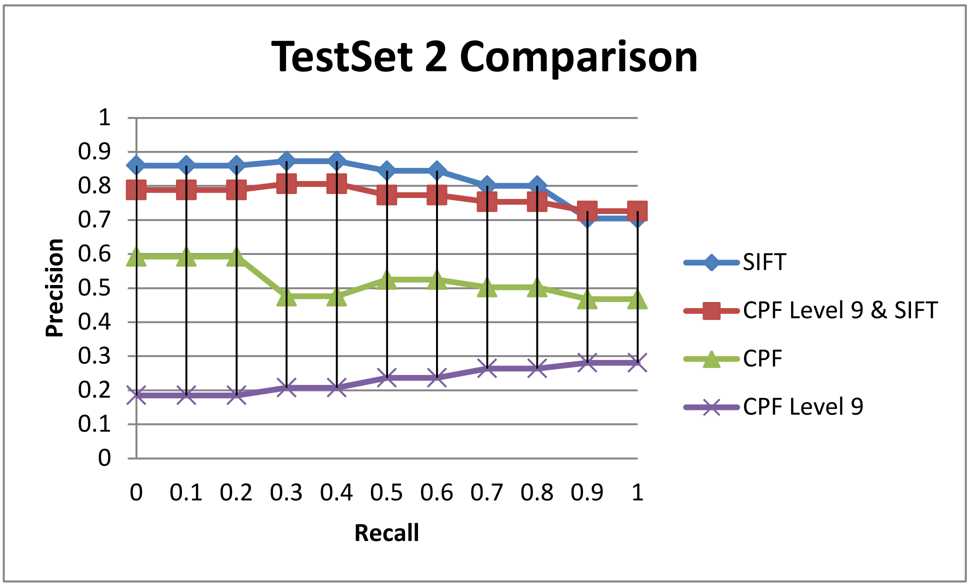


Figure 35. Precision and Recall Diagram of Test Set 2 Comparison.

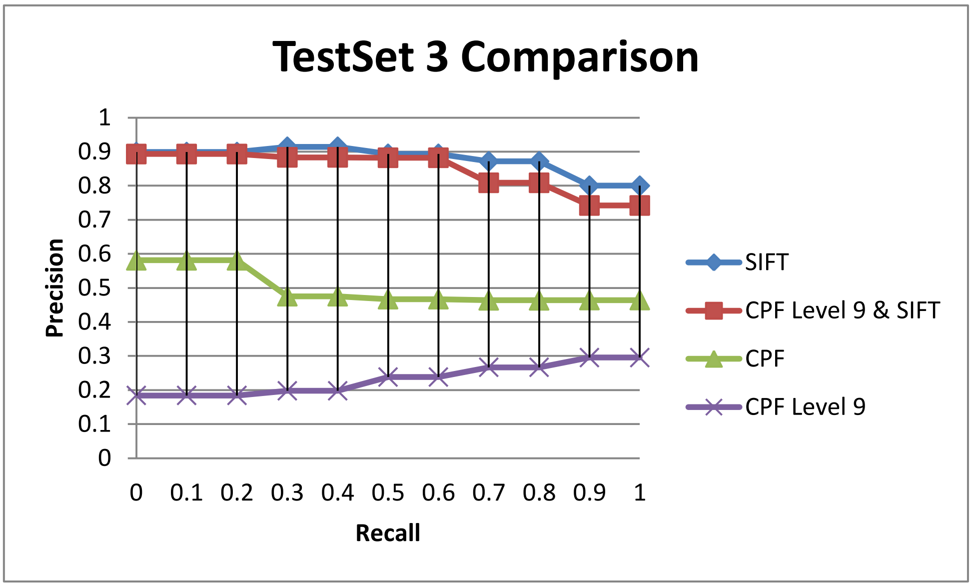


Figure 36. Precision and Recall Diagram of Test Set 3 Comparison.

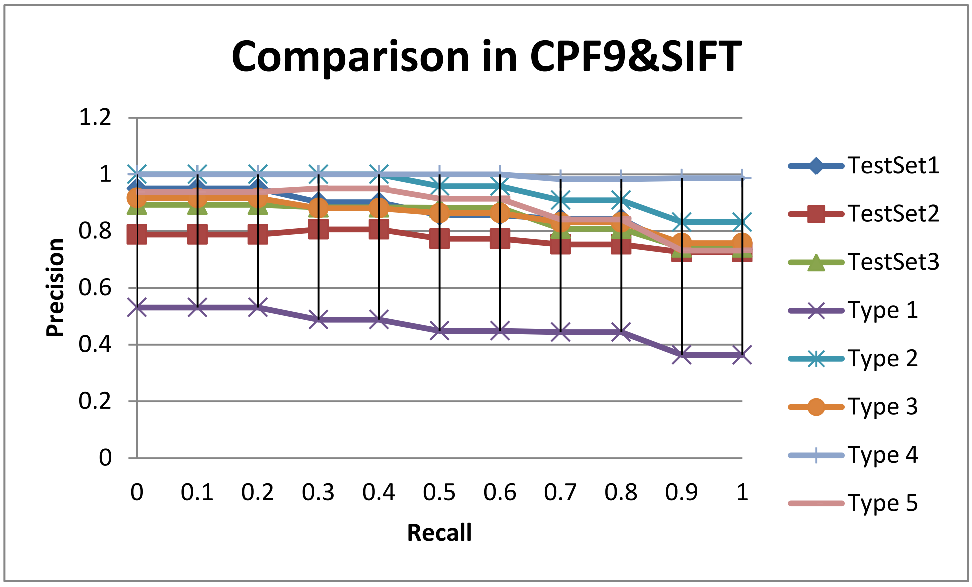


Figure 37. Precision and Recall Diagram of Comparison in CPF level 9 & SIFT.

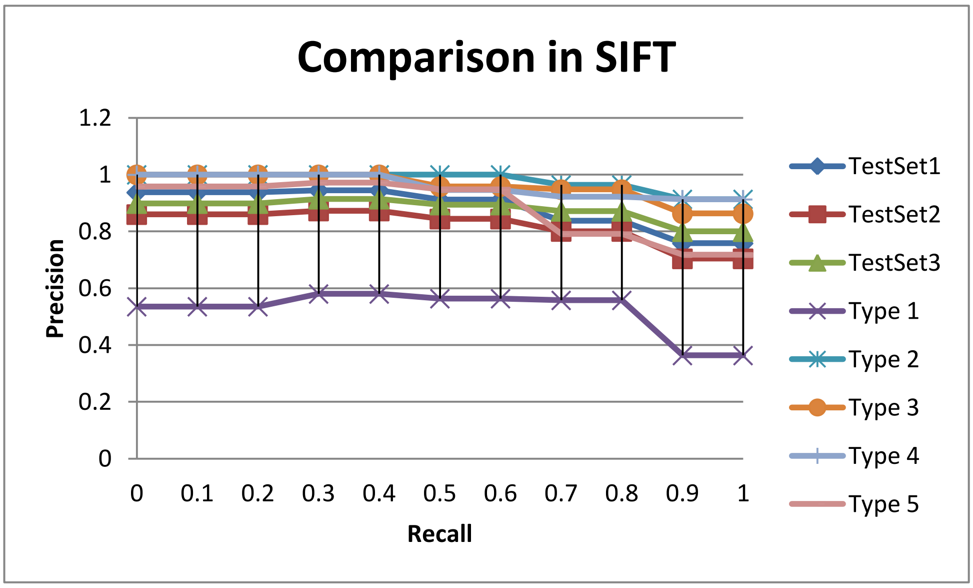


Figure 38. Precision and Recall Diagram of Comparison in SIFT.

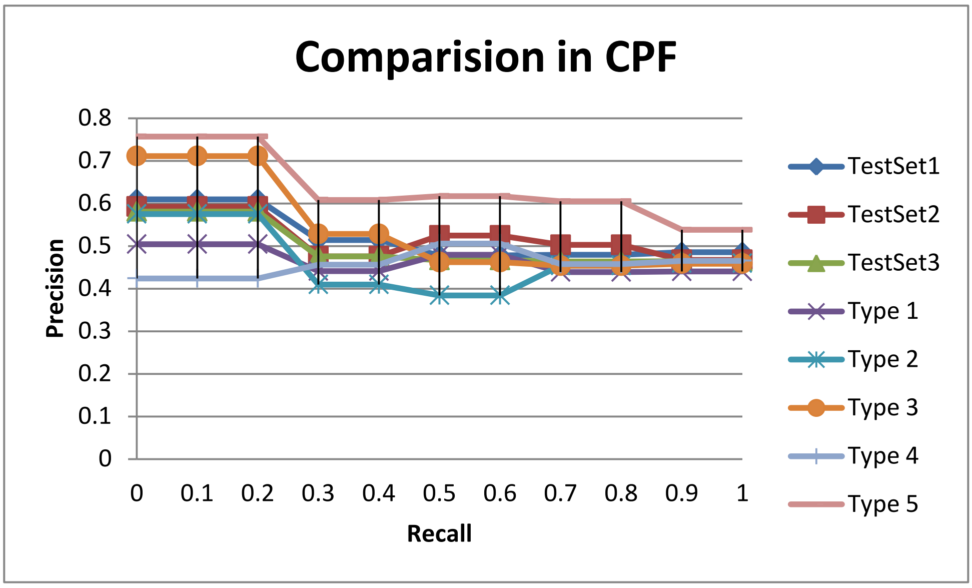


Figure 39. Precision and Recall Diagram of Comparison in CPF.

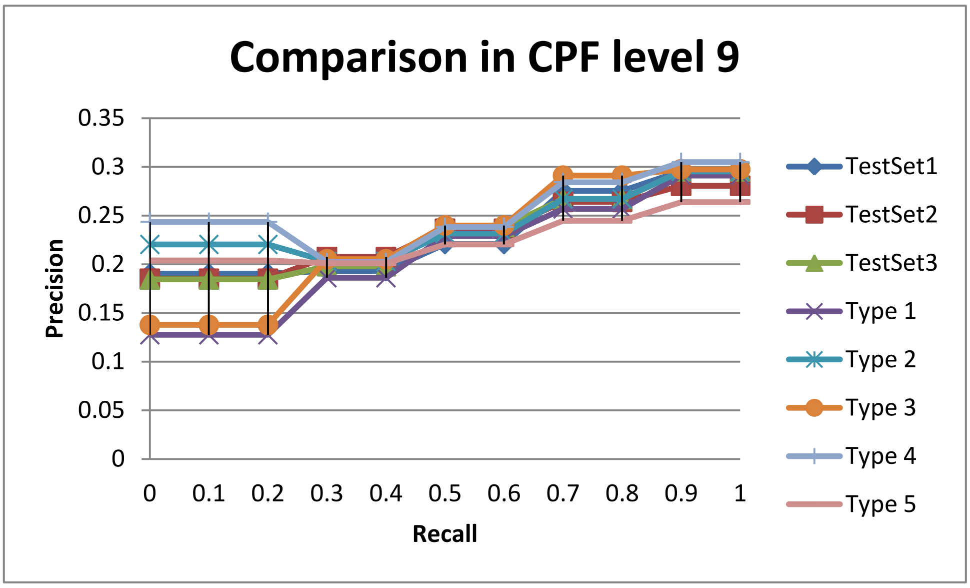


Figure 40.Precision and Recall Diagram of Comparison in CPF level 9.

From Figure 29- Figure 40, we have shown the precision and recall diagram from each methodology. Then, we can summarize the experiment result as in Table 11.

Table 11. Summarize the Performance of Three Methods.

Brand Type	CPF level9 & SIFT	SIFT	CPF/ CPF level 9
1	**Result :** Not good **Reason:** The type name of this brand is small and not clear.	**Result :** Not good **Reason:** The type name of this brand is small and not clear.	**Result :** Not good **Reason:** Many cosmetic items in this brand are similar in color and shape.
2	**Result :** High accurate **Reason:** The type name of this brand is clear and outstanding.	**Result :** High accurate **Reason:** The type name of this brand is clear and outstanding.	**Result :** Not good **Reason:** Many cosmetic items in this brand are similar in color and shape.
3	**Result :** High accurate **Reason:** The type name of this brand is clear and outstanding.	**Result :** High accurate **Reason:** The type name of this brand is clear and outstanding.	**Result :** Good **Reason:** The color and shape in this brand can classify easily.
4	**Result :** High accurate **Reason:** The type name of this brand is clear and outstanding.	**Result :** High accurate **Reason:** The type name of this brand is clear and outstanding.	**Result :** Not good **Reason:** Many cosmetic items in this brand are similar in color and shape.
5	**Result :** High accurate **Reason:** The type name of this brand is clear and outstanding.	**Result :** High accurate **Reason:** The type name of this brand is clear and outstanding.	**Result :** High accurate **Reason:** The color and shape in this brand can classify easily.

4.3.2.2. Experiment of 4 Methods Comparison

After we provide the previous experiment, we can compare all the experimental result. The performance and efficiency are shown in Figure 41.

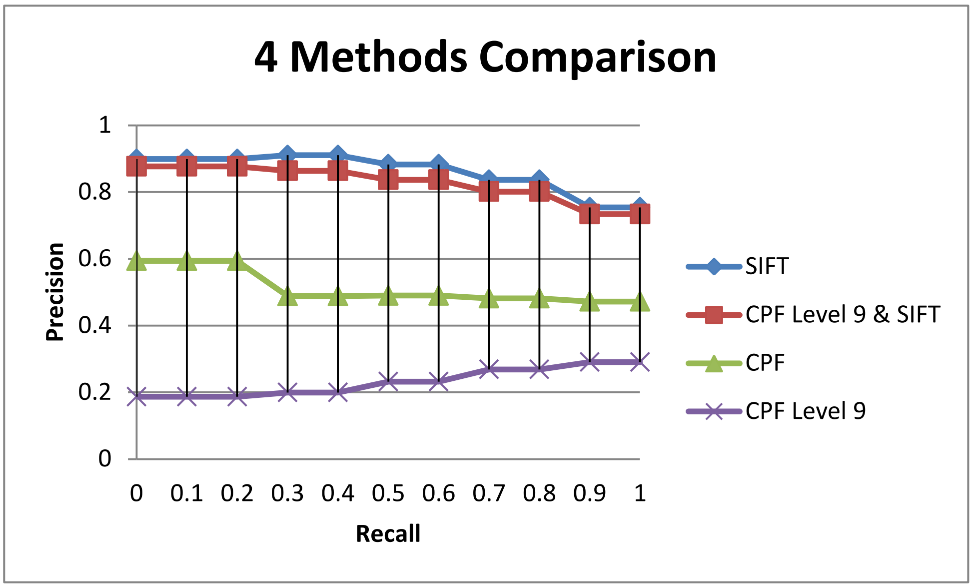


Figure 41. Precision and Recall Diagram of Comparison of 3 Methodologies.

We performed the average computation time for CPF, SIFT and CPF level 9 & SIFT as shown in Table 12 and Table 13. Then, we compared only SIFT to CPF level 9 & SIFT. We do not need to compare CPF and CPF level 9 to other methodologies because CPF uses very high computation time as shown in Figure 42.

Table 12. Comparing Average Computation Time for Each Method.

Method	Average Computation Time (s)					Average Computation Time (s)
	Brand Type 1	Brand Type 2	Brand Type 3	Brand Type 4	Brand Type 5	
CPF level 9 & SIFT	0.114	0.112	0.089	1.896	0.218	0.489
SIFT	0.232	0.228	0.182	3.900	0.392	0.987
CPF Level 9	2102.18	2312.67	2006.25	6190.71	2214.26	2965.21
CPF	2625.71	2312.62	2398.8	7748.05	2792.12	3675.46

Table 13. Comparing Average Computation Time of CPF level 9 & SIFT to Each Method.

Method	Average Computation Time (s)	Method	Average Computation Time (s)	Average Time Decrease from Each Method(%)
SIFT	0.987	CPF level 9 & SIFT	0.489	50.46
CPF Level 9	2965.21	CPF level 9 & SIFT	0.489	99.98
CPF	3675.46	CPF level 9 & SIFT	0.489	99.99

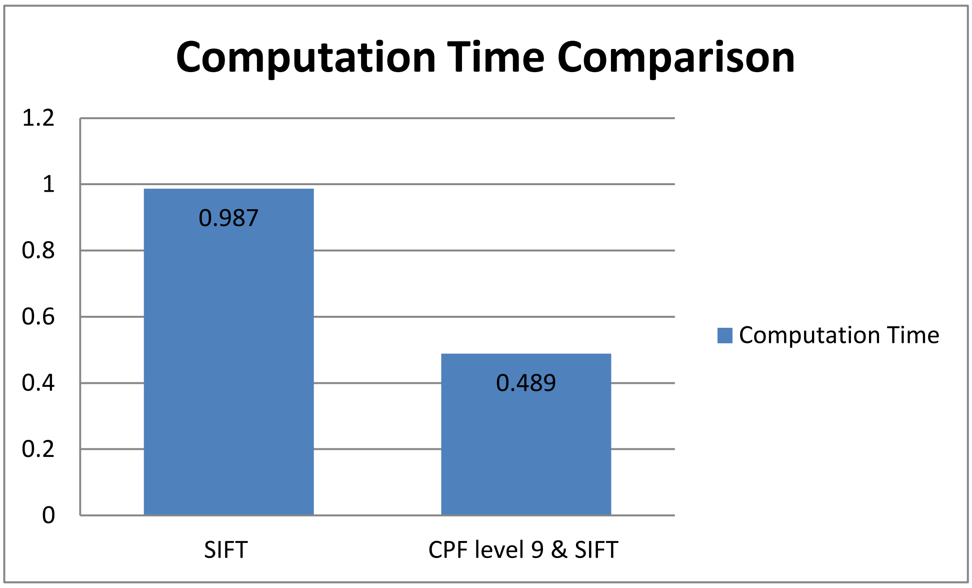
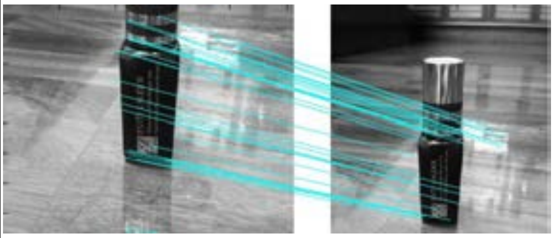


Figure 42. Comparing Computation Time of SIFT to CPF level 9 & SIFT Diagram.

4.3.3. Matching Small Part Cutting of Image

We cut a square part from complete cosmetic image. Then, we test the small part of image to image collection. The experimental result is shown in Table 14.

Table 14. Result of Square Part Cosmetic Images Match to Database.

Input Image	Complete Image	Matching Result
		
		
		
		

4.4. Discussion

According to Table 6, the CPF image pyramid of each cosmetic image (size 1024x1024) has 10 hierarchy levels. We perform the experiment on the CPF image pyramid hierarchy from level 6 (size 64x64) to level 10 (size 1024x1024). The number of matching points in the result is increased when the number of the hierarchy level is increased. Thus, the number of matching points depend on the image size.

From Figure 27, the precision and recall of CPF&SIFT level comparison shows that CPF&SIFT level 6, level 7 and level 8 have very low precision and recall. Hence, we do not select the CPF image pyramid at level 6, level 7 and level 8. However, CPF&SIFT level 9 and 10 has the high precision and recall.

Moreover, Table 7 shows that computation time also increases when the hierarchy level increases. However, computation time from level 8 to level 9 increase 23.2% but from level 9 to level 10 increase up to 116.8%. Thus, we decide to use the CPF image pyramid at level 9 to perform the next experiment.

From Table 12 and Table 13, we compare average computation time among four methodologies as CPF, CPF level 9, SIFT and CPF level 9 & SIFT. The result is CPF level 9 & SIFT can reduce SIFT computation time 50.46%. Moreover, our method can reduce CPF computation time and CPF level 9 computation times nearly 100%. Furthermore, according to Figure 42, the diagram shows that our method use less computation time than SIFT 50.46%.

The reason that CPF level 9 & SIFT is faster than SIFT about 50% is the number of interest points. SIFT use the image size of 1024x1024 pixels so the effectiveness is $O(n^2)$ when n is the number of computation pixels. On the other hand, CPF level 9 & SIFT use the filtered image with the size of 512x512 pixels so the effectiveness is $O(n^2/4)$. Hence, we improve the effectiveness from $O(n^2)$ of SIFT to $O(n^2/4)$ of CPF level 9 & SIFT because CPF can eliminate useless keypoints from the original image.

We then provide the cosmetic image matching to the database by using the CPF image pyramid at level 9. We call our methods as CPF level 9 &SIFT. The result is shown in Figure 29 to Figure 41 as a precision and recall diagram from various experiment cases.

The precision and recall of Figure 29 - Figure 33 show the result for each brand type comparison for 4 methods. Then, we summarize the result of our brand type experiment in Table 11.

In our experiment, we have 3 test set images. The diagrams shows the precision and recall for each test set images result are from Figure 34 to Figure 40. The result of test set 1, test set 2 and test set 3 shows no different in every methods. The reason is that test set 1 which contains the cosmetic images with room background and test set 2 which has a hand holding the cosmetic items have a lot of noises in the image. Thus, after the experiment, the result shows that the different in noise does not have the impact to the efficiency of our method. Last is test set 3, this test set has more illumination than test set 1 and test set 2 and the result shows that the illumination change does not make the efficiency of our method decreased. Moreover, after filtering the image by using CPF pyramid, we use SIFT to extract keypoint descriptors. That means the CPF filtered image can still keep the strong points of SIFT works as well.

Moreover, we also compare the result for each method. The precision and recall for each methods are shown in Figure 37 to 40. Then, we compare the precision and recall of 4 methods as shown in Figure 41. From these diagrams, we can conclude that our method can retrieve cosmetic images from the training database correctly compare to SIFT by precision and recall and improve in effectiveness 50.46% from SIFT.

The last experiment, we cut some part of complete Cosmetic image and then provide the experiment. The result is shown that our method can perform correctly even input image is not complete as in Table 14. Thus, user can define the size of input image by using only some part of the smallest image but still keep the prominent point of the image.

CPF level 9 & SIFT methods will give the best result when using with the cosmetic item that has outstanding brand name, logo and type information. If the brand name, logo or type information is not clear and outstanding, it is difficult to retrieve the exact cosmetic item correctly. Thus, the result will have lower precision and recall compare to outstanding brand name, logo and type information cosmetic item.

According to Table 6, Table 7 and Figure 27, the image size that will give the satisfactory result for our methods is from 256x256 pixels (CPF level 8) until 1024x1024 pixels (CPF level 10). If we use the smaller images size, it will give the very low precision and recall as shown in Figure 27. Moreover, if we use bigger image size than 1024x1024 pixels, it will cause a lot of computation time instead as shown in Table 7.

The cosmetic image with outstanding logo or brand name and type information will give the accurate result. However, from Table 11 and Table 12, if there are many information in cosmetic details, the computation time will be increased as in brand type 4. The cosmetic image with less details and information of brand name and type will give an inaccurate result or error as in brand type 1.

CHAPTER V

Summary and Future Work

Our method for Cosmetic image retrieval, by using multi-descriptors which is called CPF level 9 & SIFT, can improve the efficiency of cosmetic image retrieval by decreasing computation time and without reducing accuracy. From the experiment, CPF is used to help improve the effectiveness by providing an image pyramid, which reduces the computation time in the SIFT process. Moreover, our method preserves efficiency measure by precision and recall from the experiment comparing to SIFT.

Moreover, obtaining the image from the proper hierarchy of image pyramid can reduce the number of interest points in the scale-space extrema detection in SIFT, while still keeping the efficiency of keypoint matching as well. The reason is that CPF can extract the prominent points from the input cosmetic image, which will be used to find the keypoint descriptor in the SIFT method.

From Table 6 and Figure 27, the image size of cosmetic image would not smaller than 256x256 pixels. The reason is that smaller size image cause less accuracy. If the image size is smaller than 256x256 pixels, it will give the very low accurate result.

However, the biggest image size should be 1024x1024 pixels. That is because the image size which is bigger than 1024x1024 pixels does not increase accuracy much but waste a lot of computation time instead as shown in Table 7 and Figure 27. Thus, the image size should be between 256x256 pixels and 1024x1024 pixels, to give the satisfactory results and fast processing.

Our method, CPF level 9 & SIFT, gives the result with accuracy and fast. However, the input image should be the cosmetic image with outstanding brand name, logo and type information. On the other hand, the cosmetic image with unclear and lack of information for brand name, logo and type information would lead to low accuracy as in the experiment of brand type 1 case.

Furthermore, from the experiment, every brand types shows that CPF level 9 & SIFT gives the lower precision and recall than SIFT except brand type 4 case. The reason is that brand type 4 has a lot of outstanding features. Thus, CPF can filters the prominent points from the image that can used to extract keypoint descriptors very well. Thus, the precision and recall of CPF level 9 & SIFT of brand type 4 is higher than SIFT.

In conclusion, our research combines global feature and local feature together. We use CPF as global feature and SIFT as local feature and the experiment shows that our method can preserve efficiency and improve effectiveness.

Although our method of Cosmetic image retrieval by using multi-descriptors provides the cosmetic image retrieval with accuracy and reduced computation time. However, some cases of cosmetic image still give the low accurate result. CPF level 9&SIFT, SIFT, CPF and CPF level 9 have different good points and weak points for different cases which they can be supported each other. Thus, in future work, we plan to improve and develop our method to support various kinds of cosmetic images by using multi-descriptor which will give the better result for each case especially brand type 1 case. For example, combine more features such as shape and color to help improving brand type 1 case. However, brand type 1 cosmetic item is difficult to classify even by human's eyes. Last but not least, we can apply CPF level 9 & SIFT to other kinds of complex images such as Khon. Khon image retrieval can be divided into groups by using color or costume types. Khon has very strong outstanding characteristics with color. Thus, dividing the groups of Khon by color will give the best result because CPF has the potential to filter and extract the prominent points of Khon by color.

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APPENDIX

Table 15. Cosmetic Images Database.

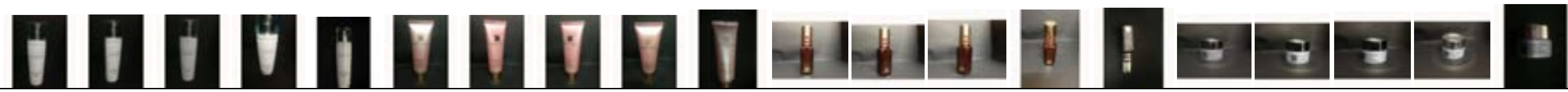
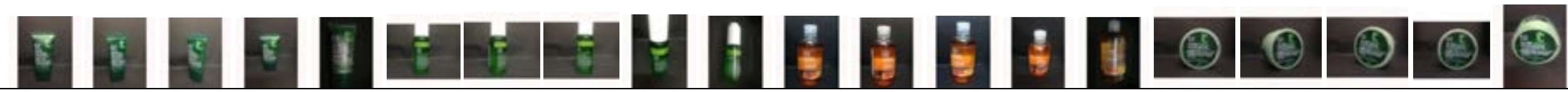
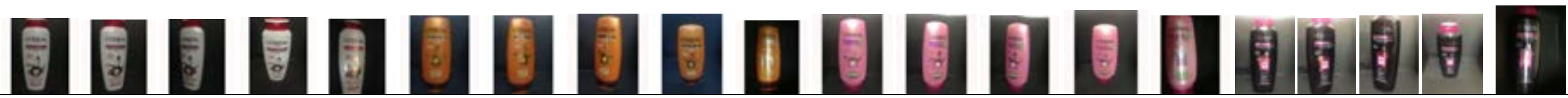
Brand Name	Images
Type 1	
Type 2	
Type 3	
Type 4	
Type 5	

Table 16. Test Set Cosmetic Images.

Test Set	Images
1	
2	
3	

Experimental Result

Table 17. Precision and Recall of CPF Level 9 & SIFT.

Recall	Precision								
	TestSet1	TestSet2	TestSet3	Type 1	Type 2	Type 3	Type 4	Type 5	Average
0.0	0.9500	0.7879	0.8930	0.5307	1.0000	0.9166	1.0000	0.9375	0.8769
0.1	0.9500	0.7879	0.8930	0.5307	1.0000	0.9166	1.0000	0.9375	0.8769
0.2	0.9500	0.7879	0.8930	0.5307	1.0000	0.9166	1.0000	0.9375	0.8769
0.3	0.9017	0.8060	0.8833	0.4879	1.0000	0.8805	1.0000	0.9500	0.8637
0.4	0.9017	0.8060	0.8833	0.4879	1.0000	0.8805	1.0000	0.9500	0.8637
0.5	0.8559	0.7727	0.8821	0.4485	0.9583	0.8631	1.0000	0.9145	0.8369
0.6	0.8559	0.7727	0.8821	0.4485	0.9583	0.8631	1.0000	0.9145	0.8369
0.7	0.8428	0.7531	0.8086	0.4435	0.9087	0.8305	0.9833	0.8414	0.8015
0.8	0.8428	0.7531	0.8086	0.4435	0.9087	0.8305	0.9833	0.8414	0.8015
0.9	0.7342	0.7258	0.7419	0.3633	0.8313	0.7577	0.9860	0.7314	0.7339
1.0	0.7342	0.7258	0.7419	0.3633	0.8313	0.7577	0.9860	0.7314	0.7339

Table 18. Precision and Recall of SIFT.

Recall	Precision								
	TestSet1	TestSet2	TestSet3	Type 1	Type 2	Type 3	Type 4	Type 5	Average
0.0	0.9375	0.8600	0.8988	0.5355	1.0000	1.0000	1.0000	0.9583	0.8987
0.1	0.9375	0.8600	0.8988	0.5355	1.0000	1.0000	1.0000	0.9583	0.8987
0.2	0.9375	0.8600	0.8988	0.5355	1.0000	1.0000	1.0000	0.9583	0.8987
0.3	0.9444	0.8726	0.9144	0.5803	1.0000	1.0000	1.0000	0.9722	0.9105
0.4	0.9444	0.8726	0.9144	0.5803	1.0000	1.0000	1.0000	0.9722	0.9105
0.5	0.9115	0.8443	0.8936	0.5637	1.0000	0.9583	0.9458	0.9479	0.8831
0.6	0.9115	0.8443	0.8936	0.5637	1.0000	0.9583	0.9458	0.9479	0.8831
0.7	0.8376	0.8007	0.8715	0.5578	0.9642	0.9475	0.9225	0.7908	0.8366
0.8	0.8376	0.8007	0.8715	0.5578	0.9642	0.9475	0.9225	0.7908	0.8366
0.9	0.7585	0.7042	0.7999	0.3635	0.9136	0.8630	0.9131	0.7177	0.7542
1.0	0.7585	0.7042	0.7999	0.3635	0.9136	0.8630	0.9131	0.7177	0.7542

Table 19. Precision and Recall of CPF.

Recall	Precision								
	TestSet1	TestSet2	TestSet3	Type 1	Type 2	Type 3	Type 4	Type 5	Average
0.0	0.6093	0.5925	0.5810	0.5042	0.5751	0.7111	0.4239	0.7569	0.5942
0.1	0.6093	0.5925	0.5810	0.5042	0.5751	0.7111	0.4239	0.7569	0.5942
0.2	0.6093	0.5925	0.5810	0.5042	0.5751	0.7111	0.4239	0.7569	0.5942
0.3	0.5143	0.4756	0.4756	0.4408	0.4096	0.5281	0.4557	0.6083	0.4885
0.4	0.5143	0.4756	0.4756	0.4408	0.4096	0.5281	0.4557	0.6083	0.4885
0.5	0.4778	0.5246	0.4669	0.4797	0.3842	0.4620	0.5057	0.6172	0.4897
0.6	0.4778	0.5246	0.4669	0.4797	0.3842	0.4620	0.5057	0.6172	0.4897
0.7	0.4791	0.5025	0.4634	0.4386	0.4539	0.4535	0.4576	0.6048	0.4817
0.8	0.4791	0.5025	0.4634	0.4386	0.4539	0.4535	0.4576	0.6048	0.4817
0.9	0.4851	0.4673	0.4643	0.4400	0.4595	0.4586	0.4654	0.5377	0.4722
1.0	0.4851	0.4673	0.4643	0.4400	0.4595	0.4586	0.4654	0.5377	0.4722

Table 20. Precision and Recall of CPF Level 9.

Recall	Precision								
	TestSet1	TestSet2	TestSet3	Type 1	Type 2	Type 3	Type 4	Type 5	Average
0.0	0.1901	0.1849	0.1842	0.1274	0.2201	0.1375	0.2434	0.2036	0.1864
0.1	0.1901	0.1849	0.1842	0.1274	0.2201	0.1375	0.2434	0.2036	0.1864
0.2	0.1901	0.1849	0.1842	0.1274	0.2201	0.1375	0.2434	0.2036	0.1864
0.3	0.1928	0.2072	0.1978	0.1860	0.2027	0.2050	0.2020	0.2007	0.1993
0.4	0.1928	0.2072	0.1978	0.1860	0.2027	0.2050	0.2020	0.2007	0.1993
0.5	0.2206	0.2363	0.2382	0.2289	0.2316	0.2397	0.2381	0.2201	0.2317
0.6	0.2206	0.2363	0.2382	0.2289	0.2316	0.2397	0.2381	0.2201	0.2317
0.7	0.2751	0.2638	0.2669	0.2567	0.2668	0.2908	0.2841	0.2445	0.2686
0.8	0.2751	0.2638	0.2669	0.2567	0.2668	0.2908	0.2841	0.2445	0.2686
0.9	0.2954	0.2804	0.2953	0.2910	0.2951	0.2973	0.3048	0.2637	0.2904
1.0	0.2954	0.2804	0.2953	0.2910	0.2951	0.2973	0.3048	0.2637	0.2904

CPF level 9&SIFT

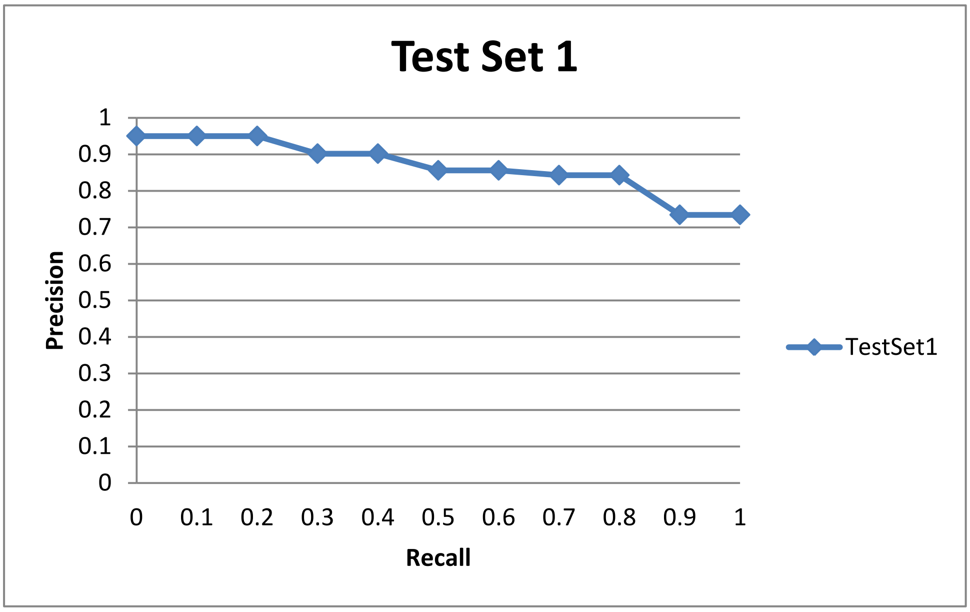


Figure 43. Precision and Recall Diagram of Test Set 1 of CPF level 9 & SIFT.

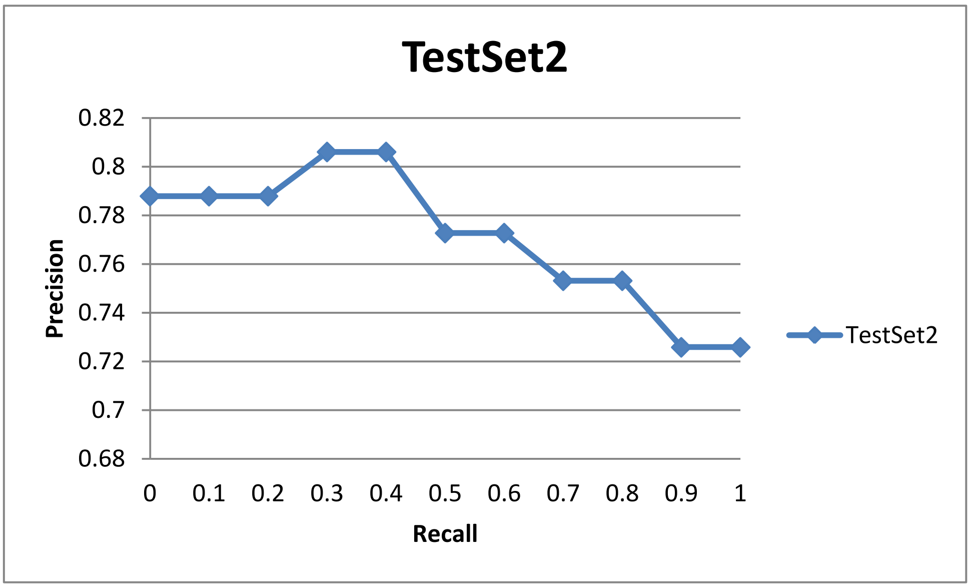


Figure 44. Precision and Recall Diagram of Test Set 2 of CPF level 9 & SIFT.

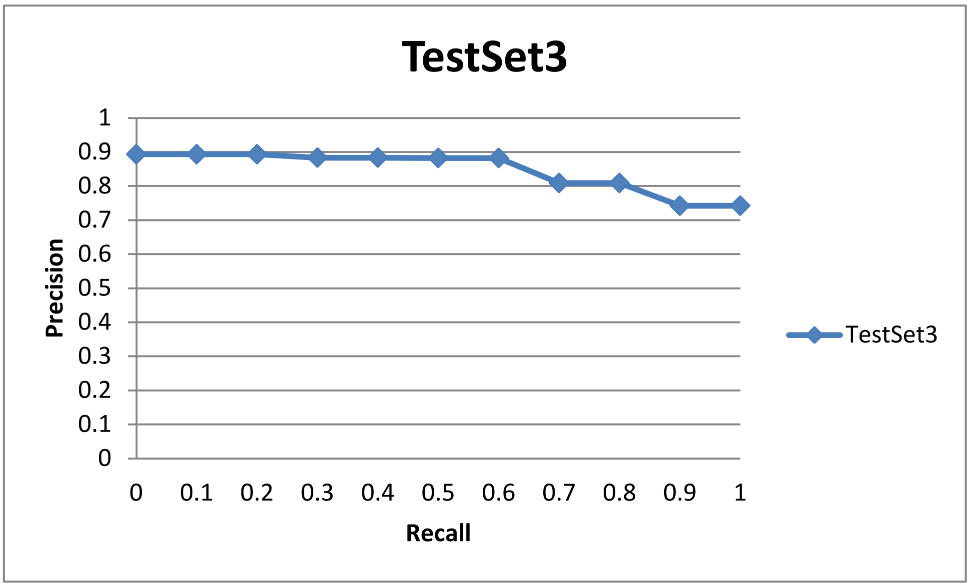


Figure 45. Precision and Recall Diagram of Test Set 3 of CPF level 9 & SIFT.

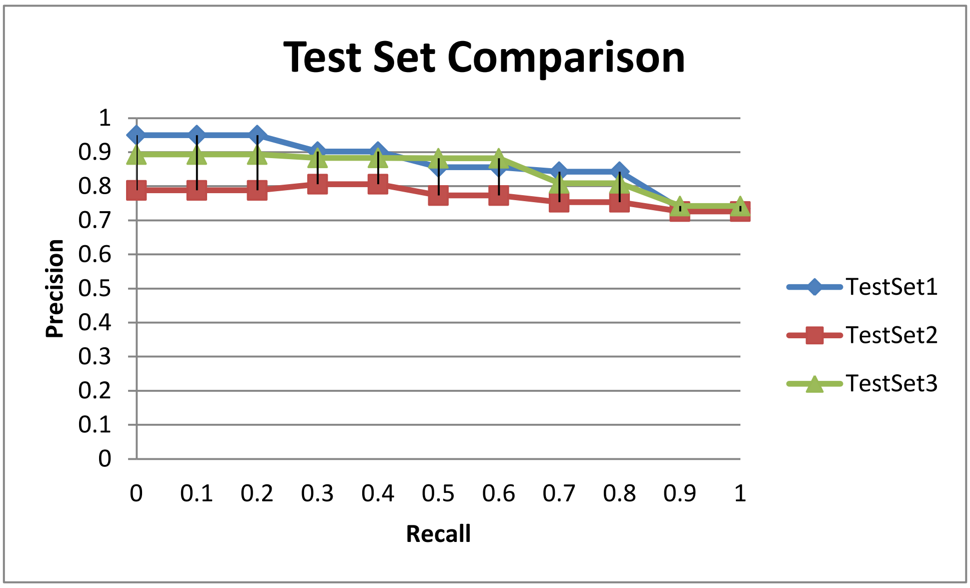


Figure 46. Precision and Recall Diagram of Test Set Comparison of CPF level 9 & SIFT.

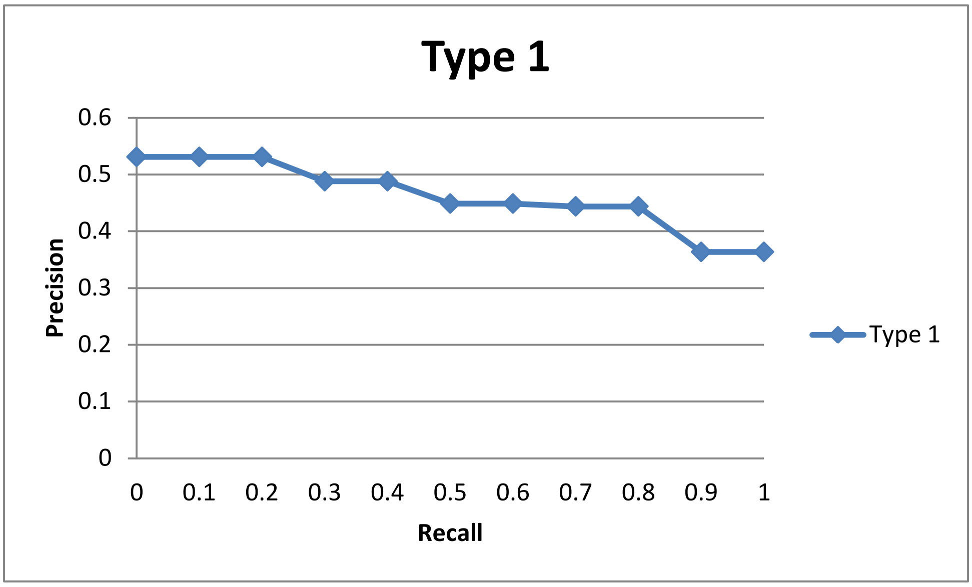


Figure 47. Precision and Recall Diagram of Type 1 of CPF level 9 & SIFT.

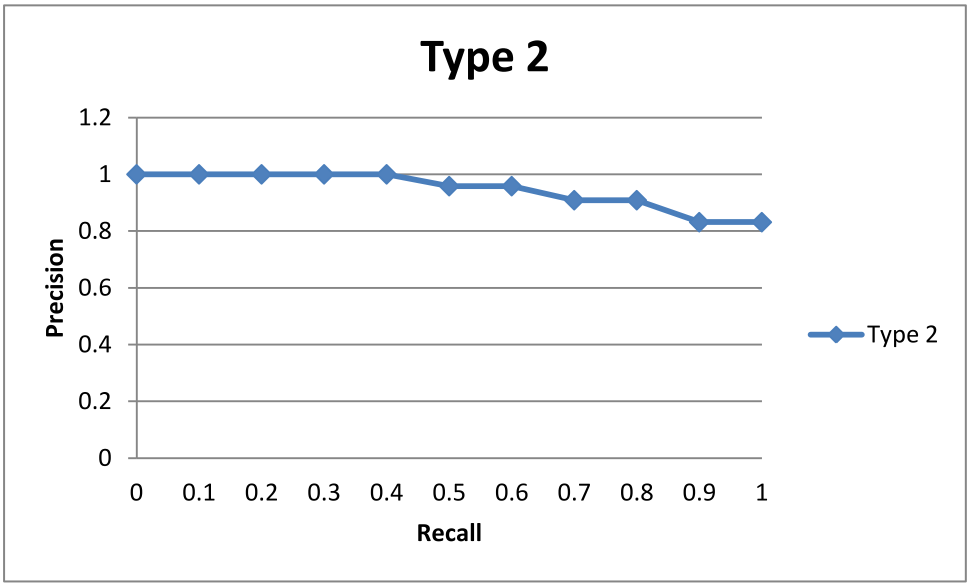


Figure 48. Precision and Recall Diagram of Type 2 of CPF level 9 & SIFT.

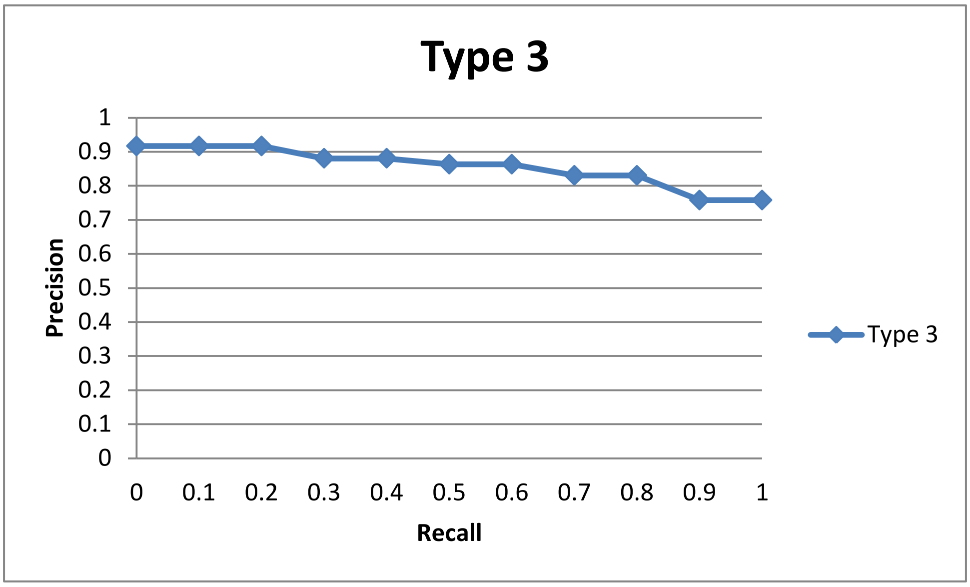


Figure 49. Precision and Recall Diagram of Type 3 of CPF level 9 & SIFT.

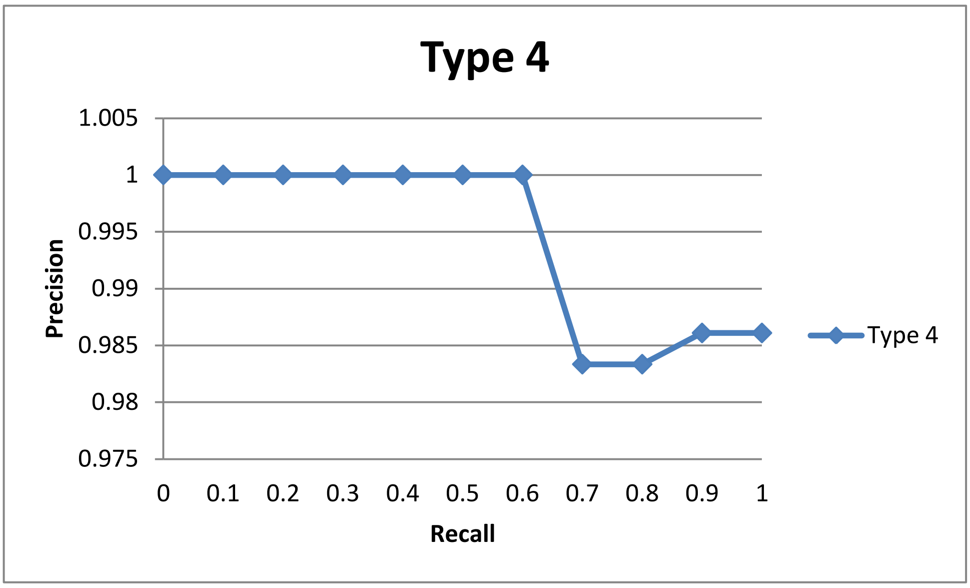


Figure 50. Precision and Recall Diagram of Type 4 of CPF level 9 & SIFT.

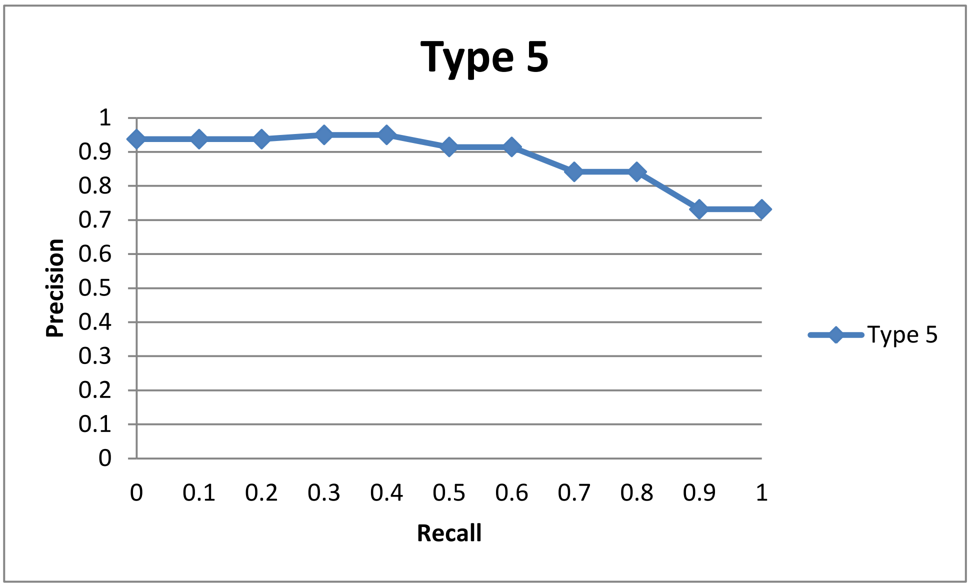


Figure 51. Precision and Recall Diagram of Type 5 of CPF level 9 & SIFT.

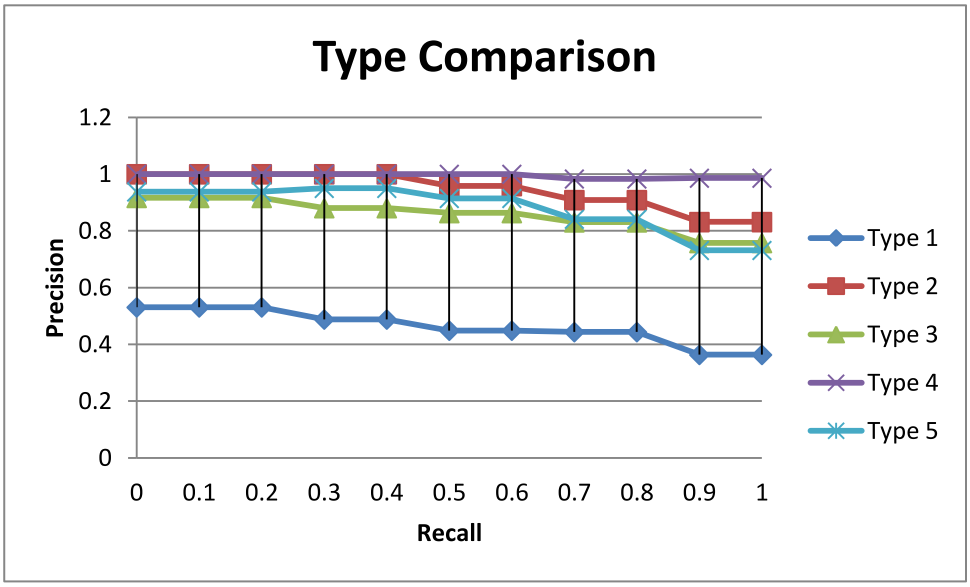


Figure 52. Precision and Recall Diagram of Type Comparison of CPF level 9 & SIFT.

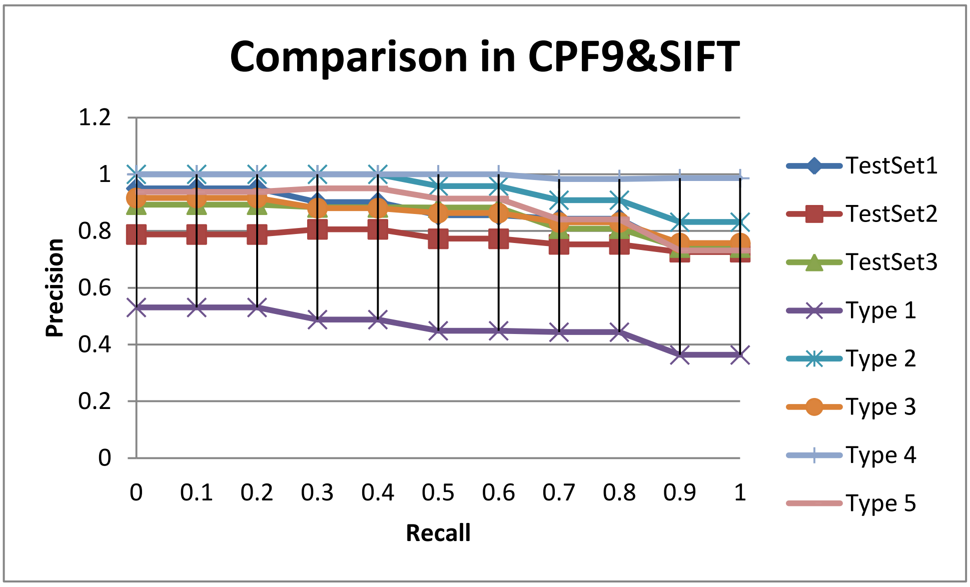


Figure 53. Precision and Recall Diagram of Comparison in CPF level 9 & SIFT.

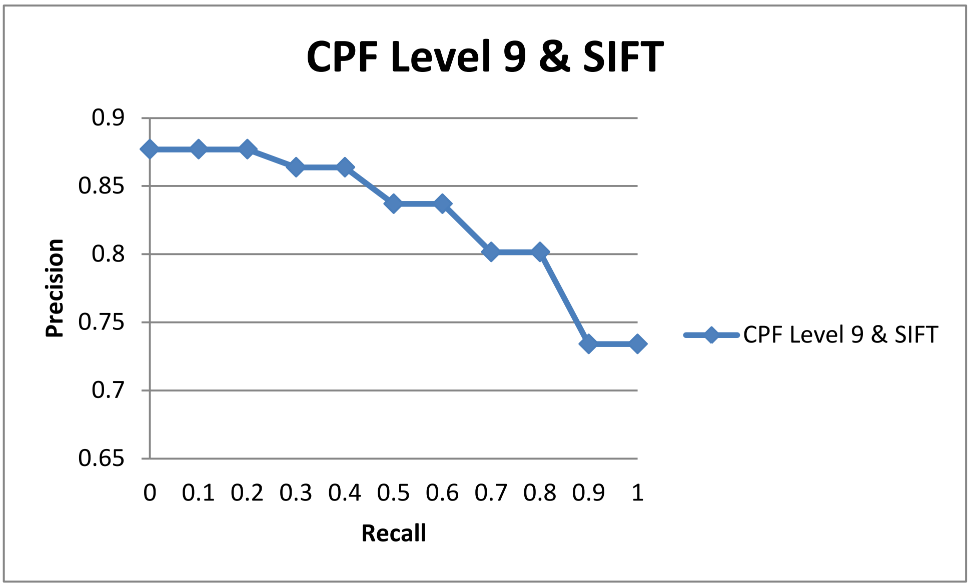


Figure 54. Precision and Recall Diagram of CPF level 9 & SIFT.

SIFT

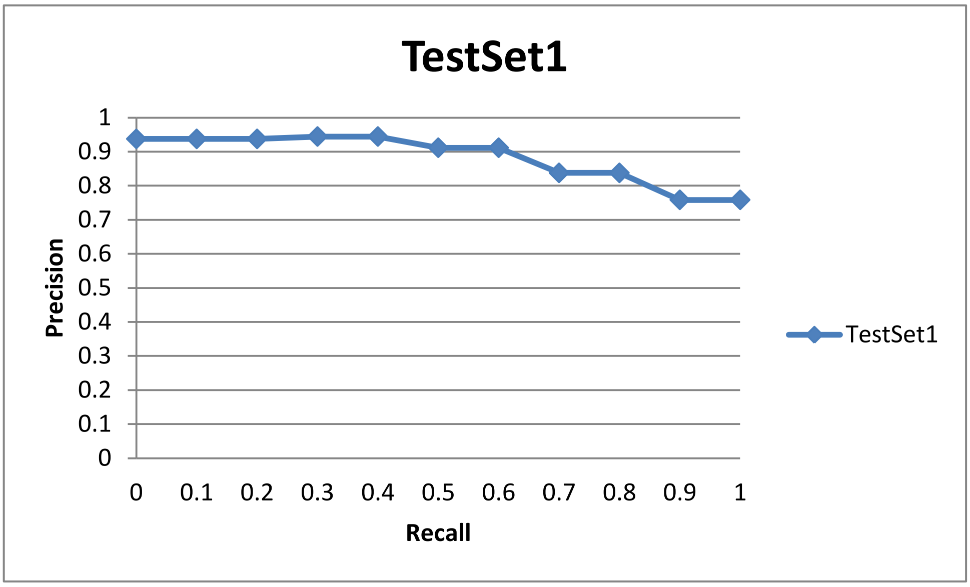


Figure 55. Precision and Recall Diagram of Test Set 1 of SIFT.

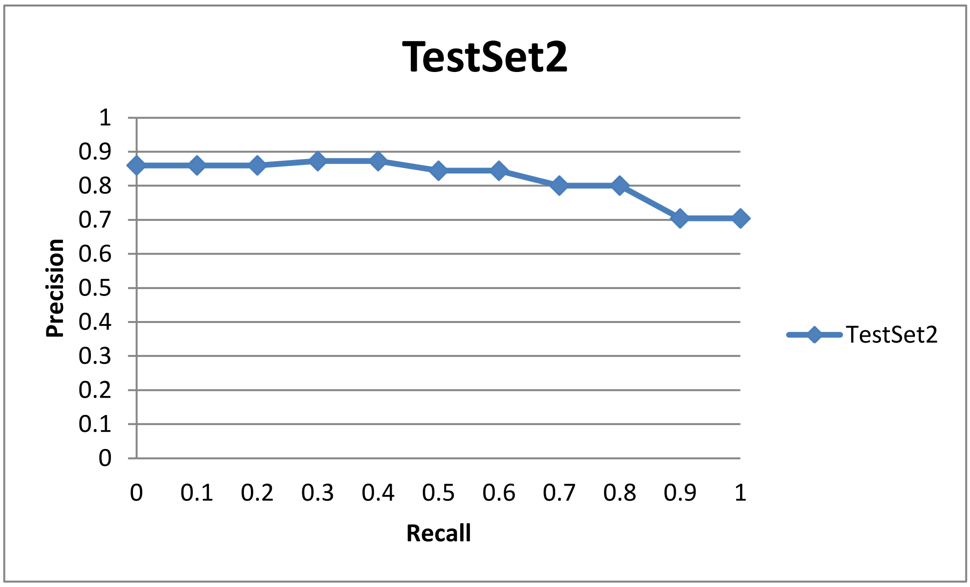


Figure 56. Precision and Recall Diagram of Test Set 2 of SIFT.

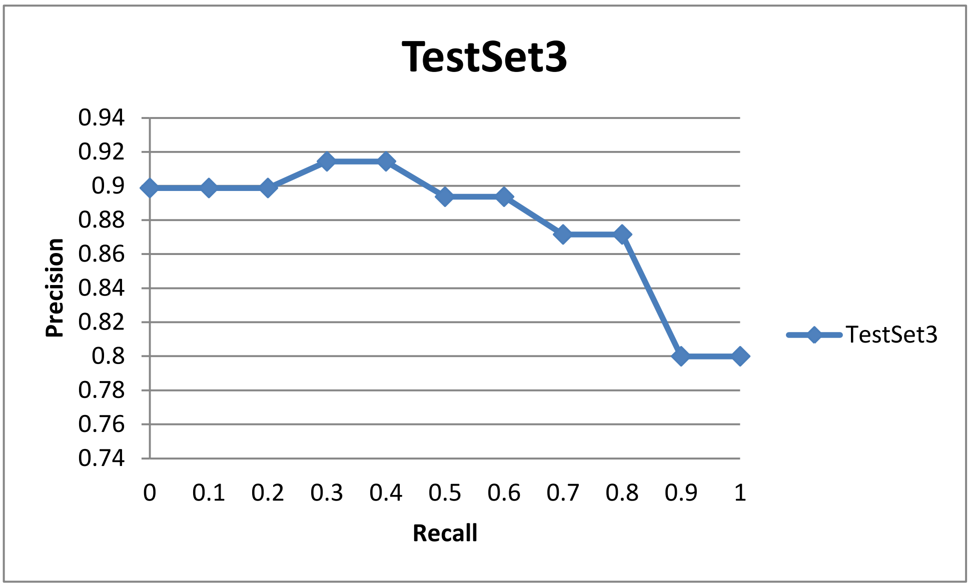


Figure 57. Precision and Recall Diagram of Test Set 3 of SIFT.

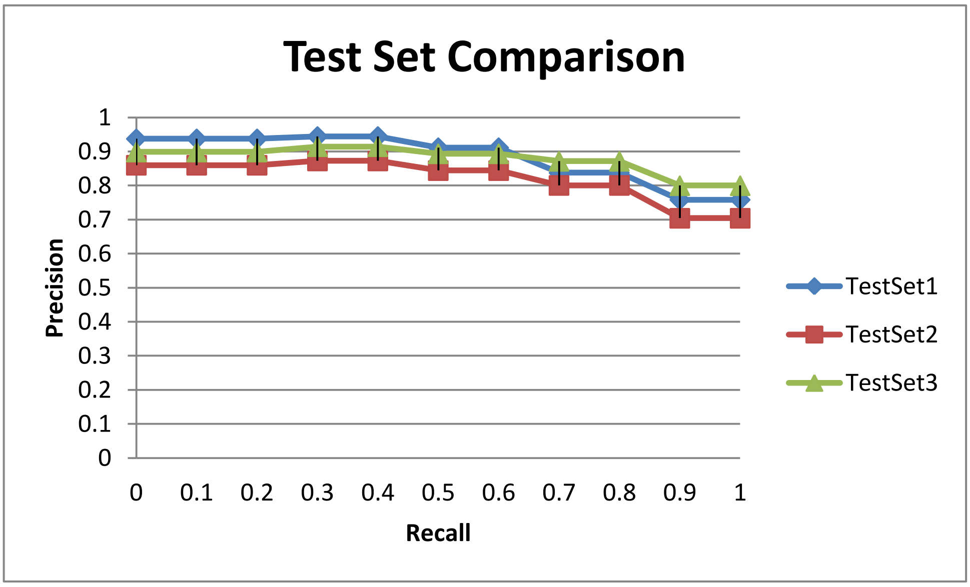


Figure 58. Precision and Recall Diagram of Test Set Comparison of SIFT.

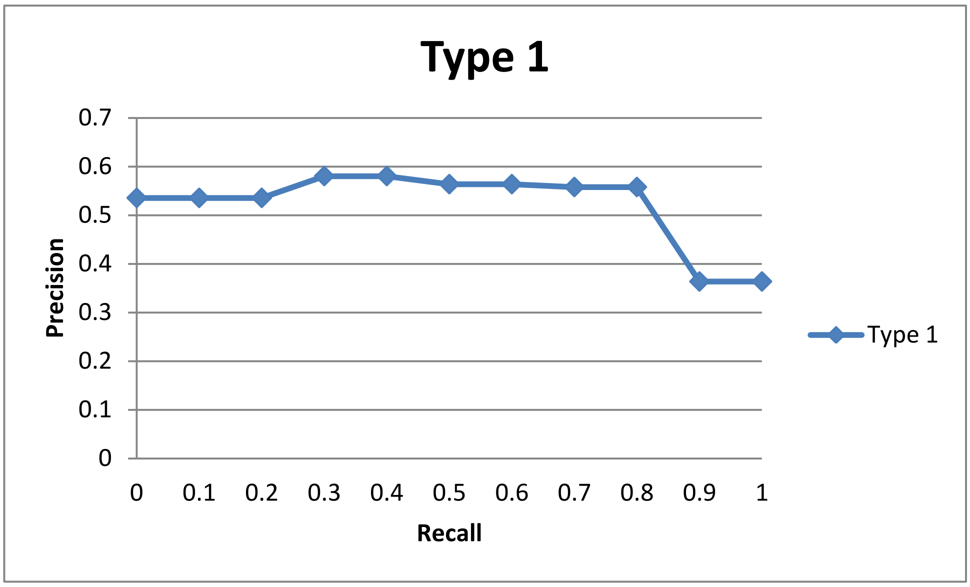


Figure 59. Precision and Recall Diagram of Type 1 of SIFT.

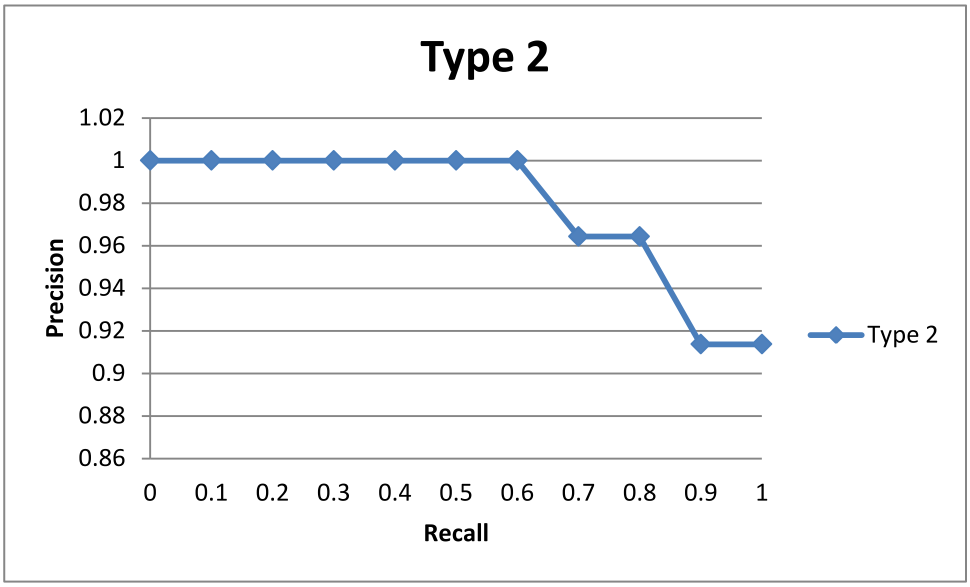


Figure 60. Precision and Recall Diagram of Type 2 of SIFT.

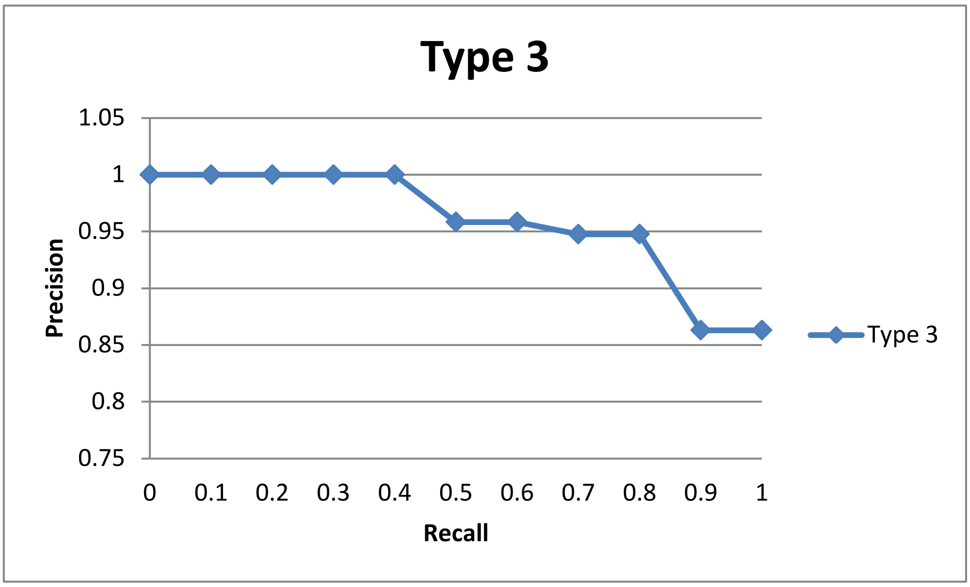


Figure 61. Precision and Recall Diagram of Type 3 of SIFT.

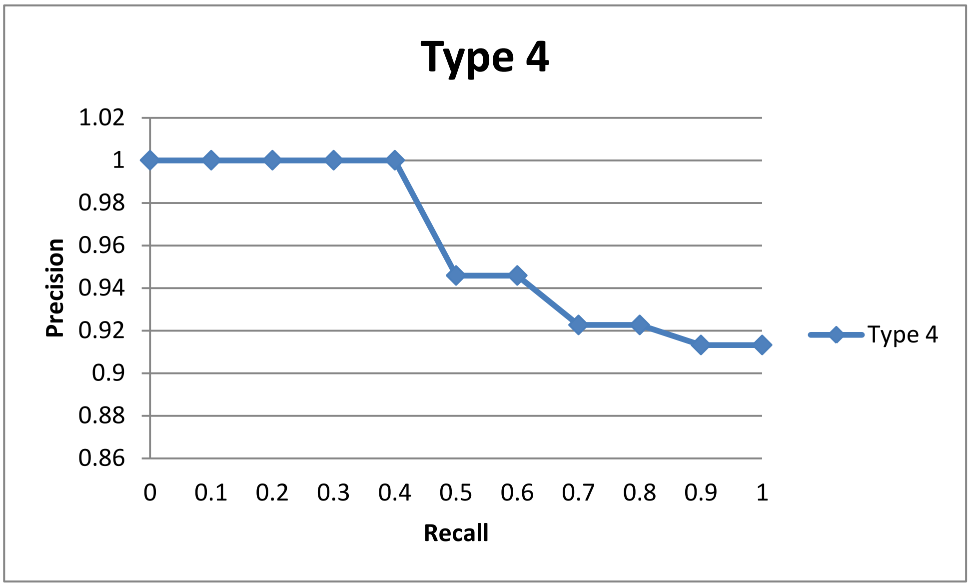


Figure 62. Precision and Recall Diagram of Type 4 of SIFT.

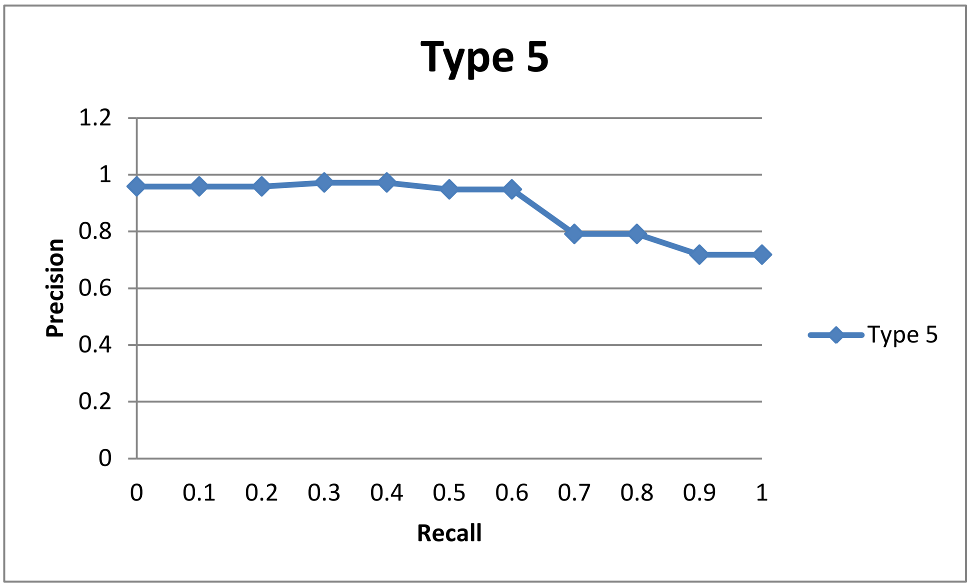


Figure 63. Precision and Recall Diagram of Type 5 of SIFT.

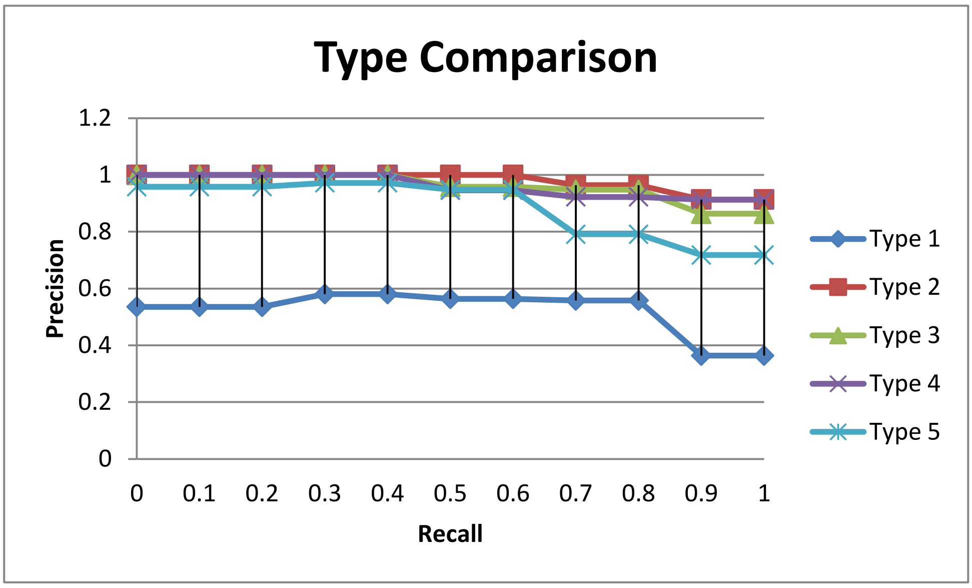


Figure 64. Precision and Recall Diagram of Type Comparison of SIFT.

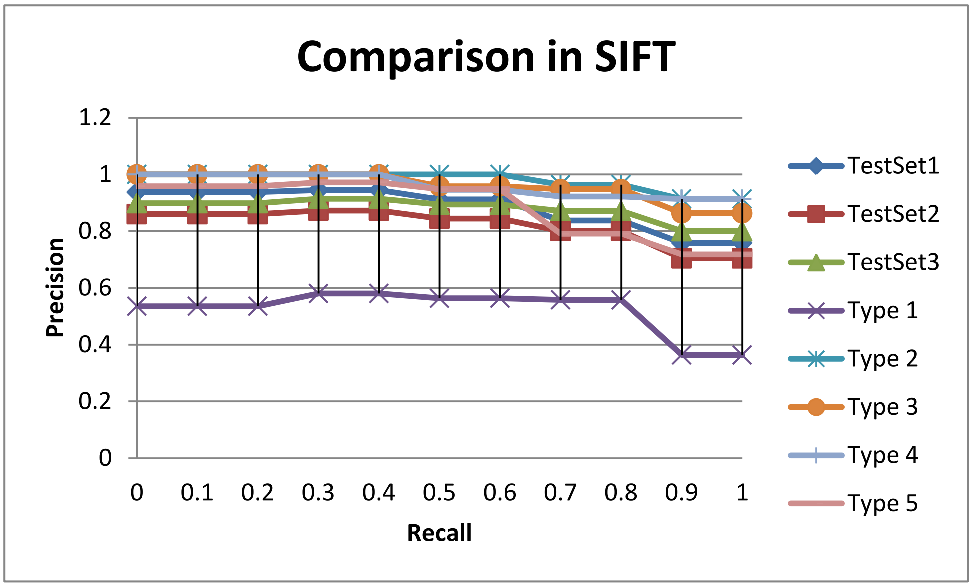


Figure 65. Precision and Recall Diagram of Comparison in SIFT.

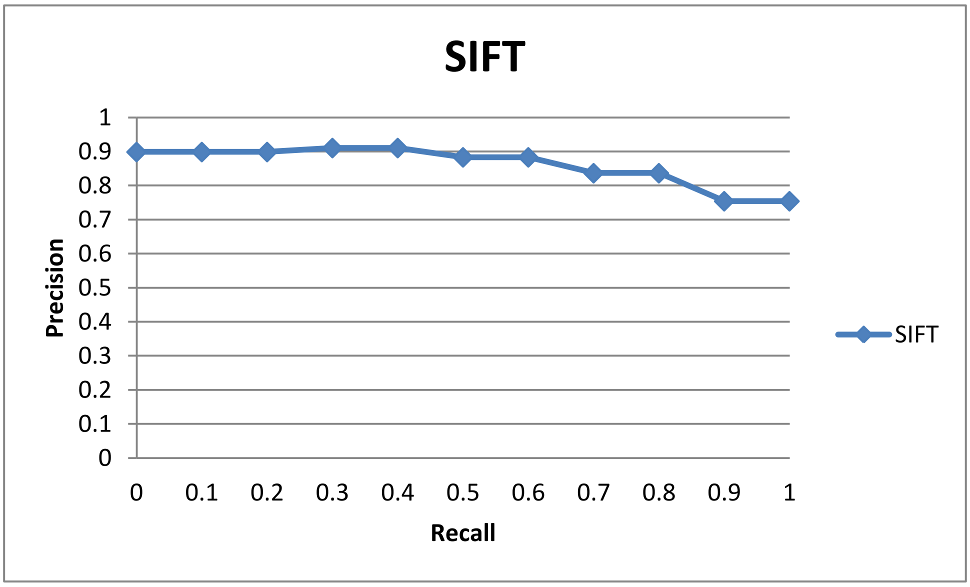


Figure 66. Precision and Recall Diagram of SIFT.

CPF

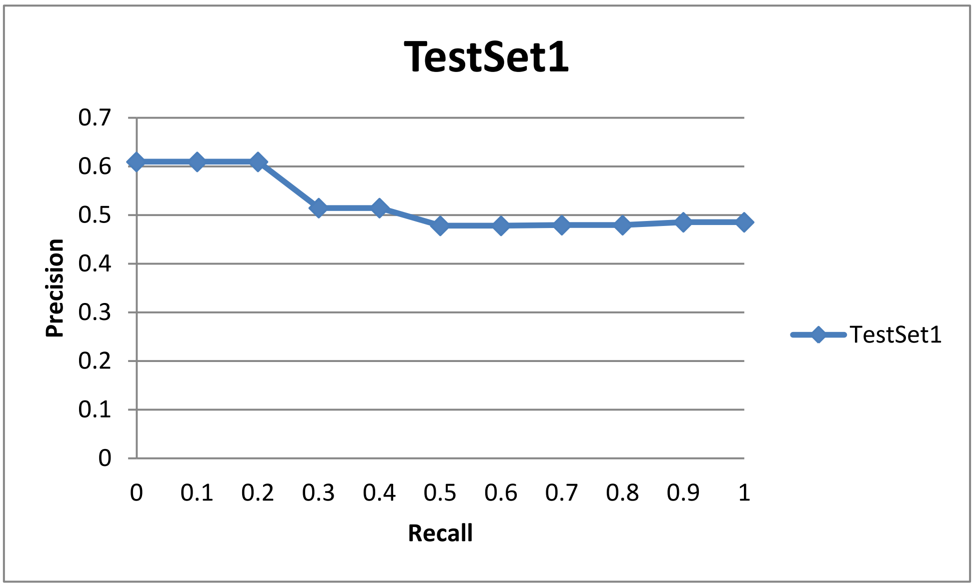


Figure 67. Precision and Recall Diagram of Test Set 1 of CPF.

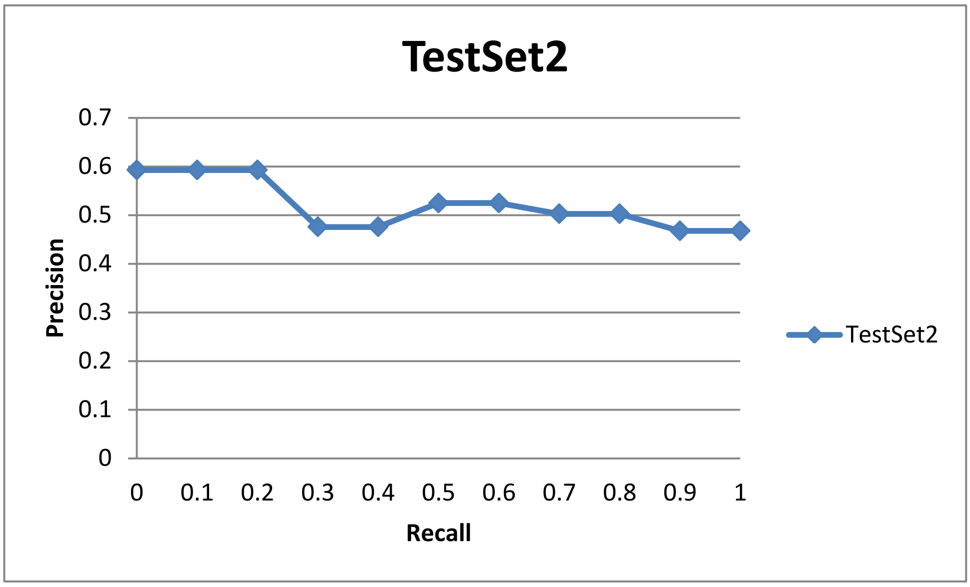


Figure 68. Precision and Recall Diagram of Test Set 2 of CPF.

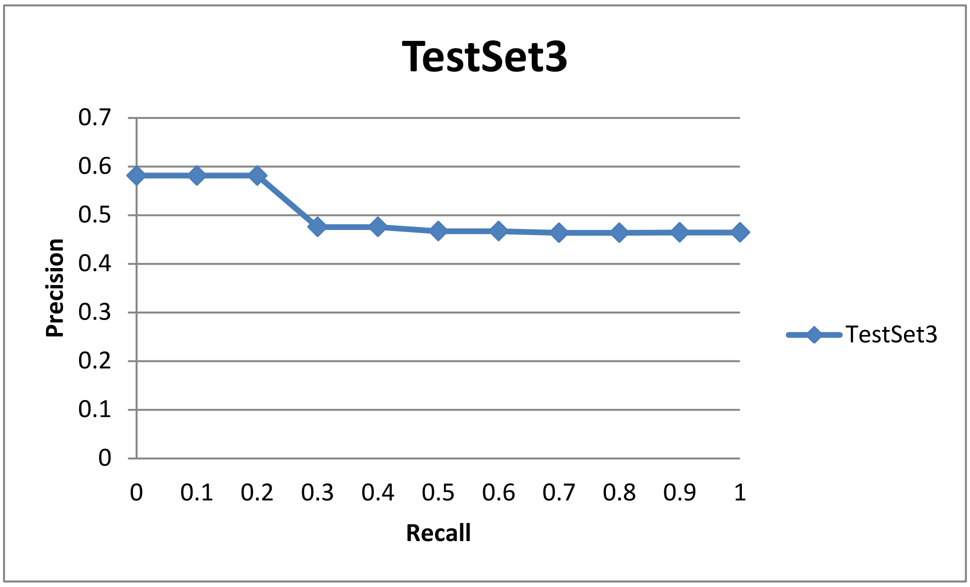


Figure 69. Precision and Recall Diagram of Test Set 3 of CPF.

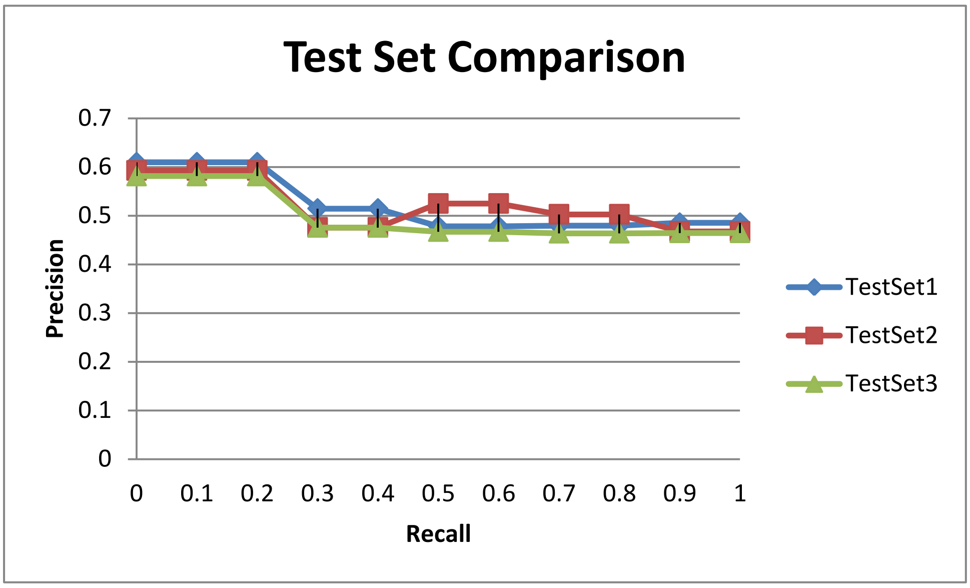


Figure 70. Precision and Recall Diagram of Test Set Comparison of CPF.

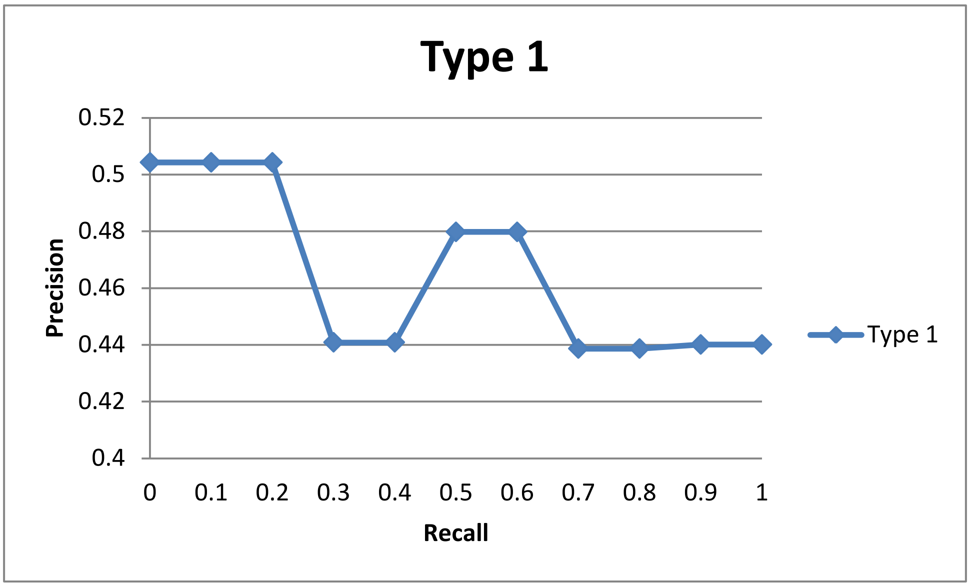


Figure 71. Precision and Recall Diagram of Type 1 of CPF.

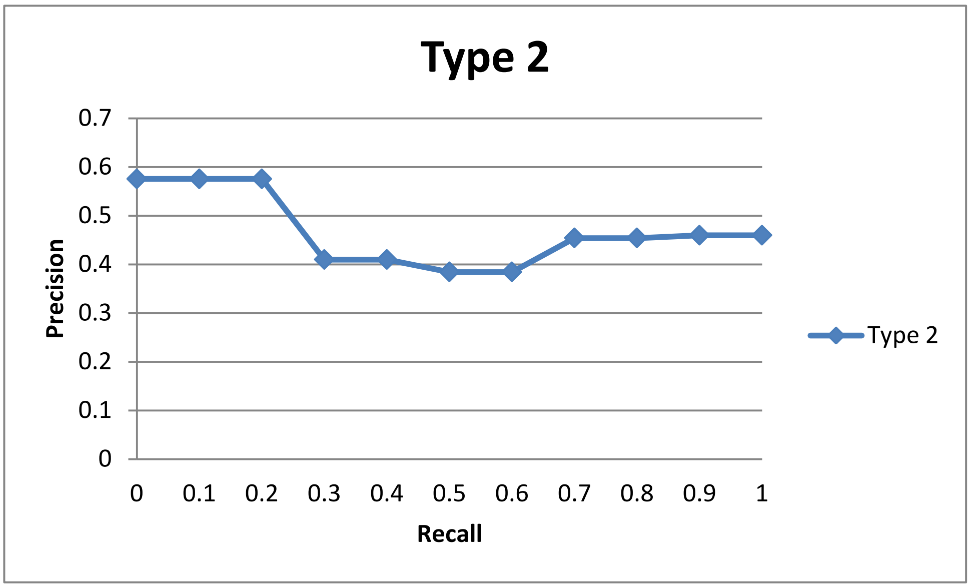


Figure 72. Precision and Recall Diagram of Type 2 of CPF.

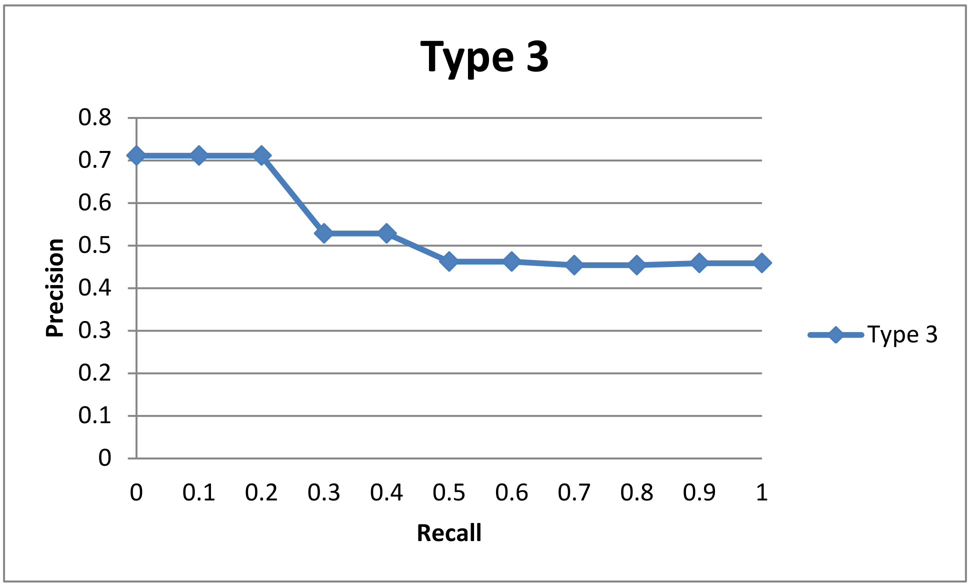


Figure 73. Precision and Recall Diagram of Type 3 of CPF.

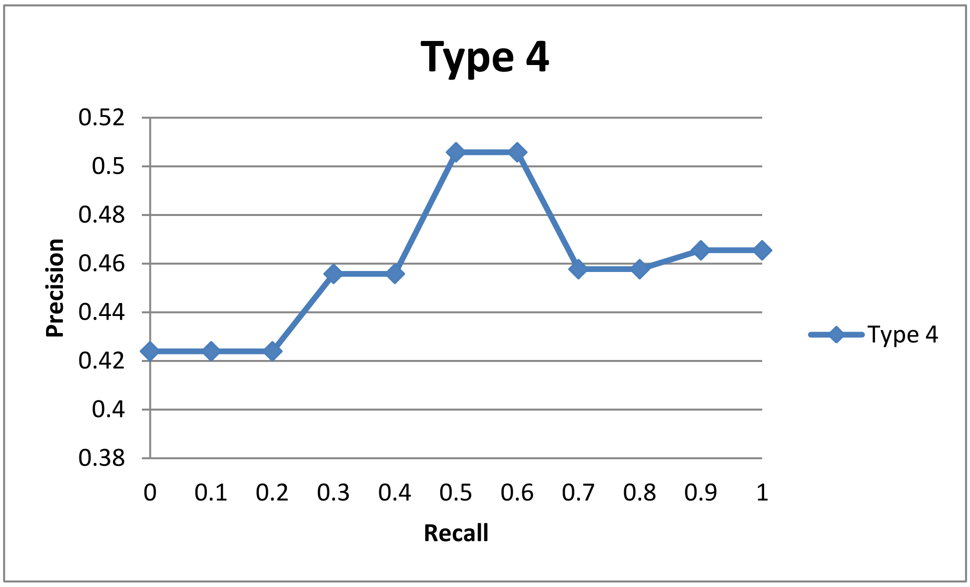


Figure 74. Precision and Recall Diagram of Type 4 of CPF.

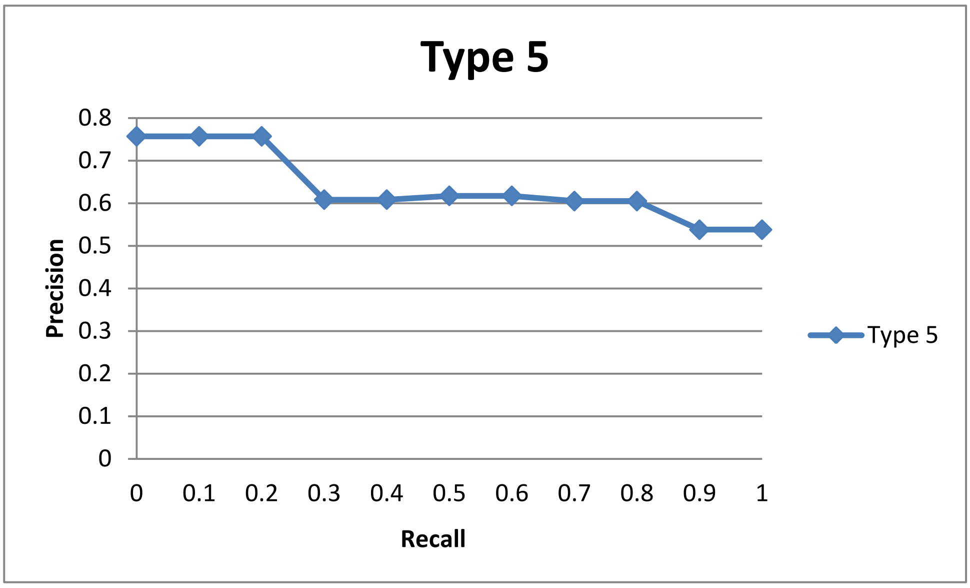


Figure 75. Precision and Recall Diagram of Type 5 of CPF.

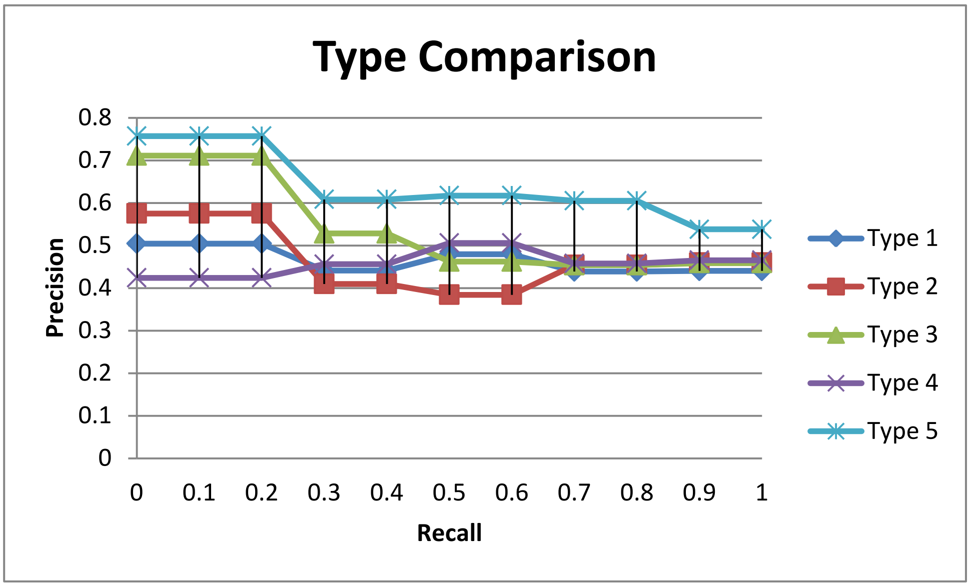


Figure 76. Precision and Recall Diagram of Type Comparison of CPF.

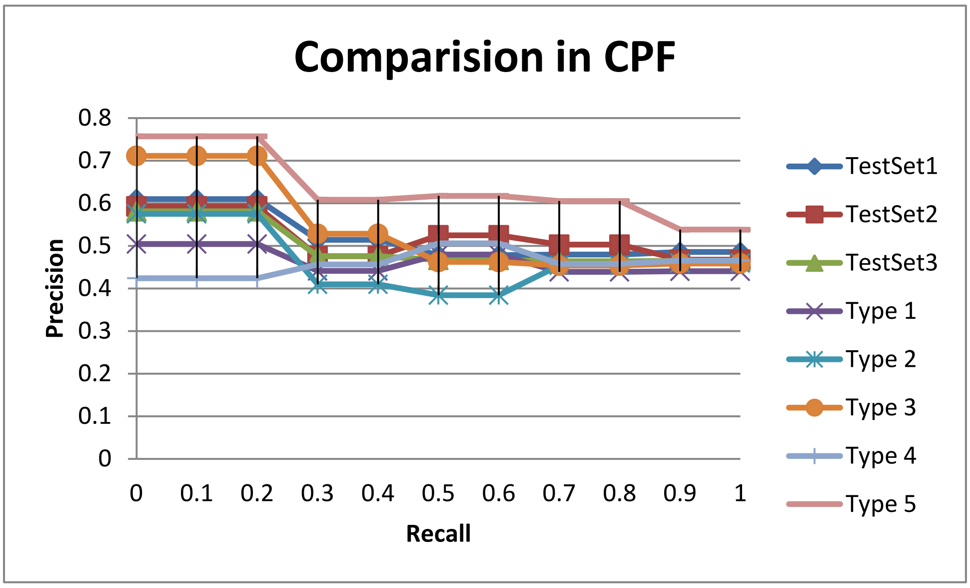


Figure 77. Precision and Recall Diagram of Comparison in CPF.

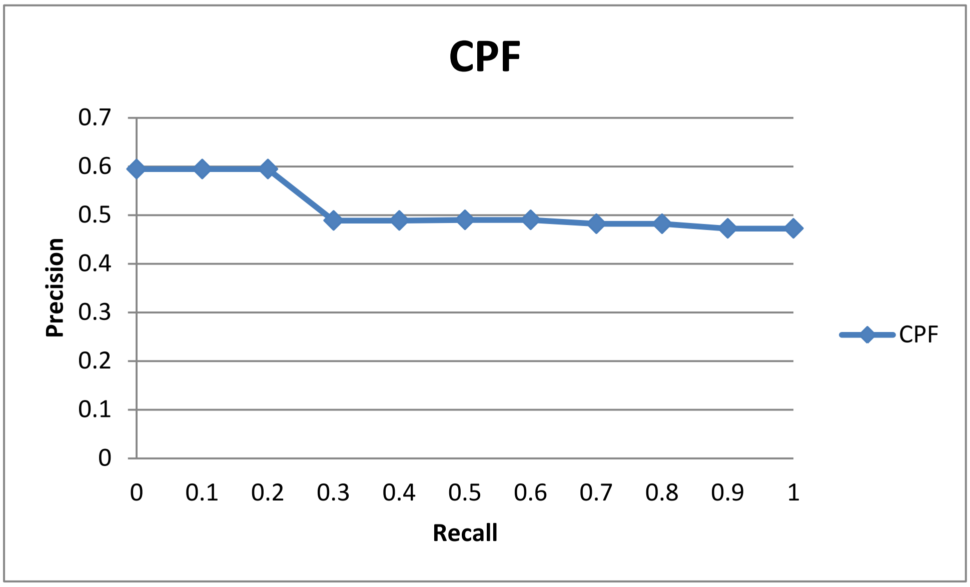


Figure 78. Precision and Recall Diagram of CPF.

CPF Level 9

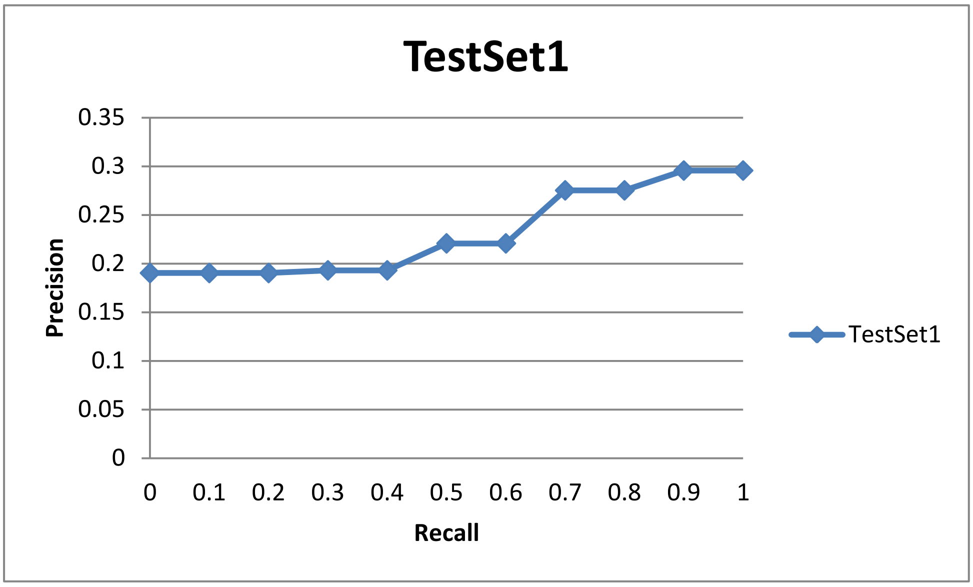


Figure 79. Precision and Recall Diagram of Test Set 1 of CPF Level 9.

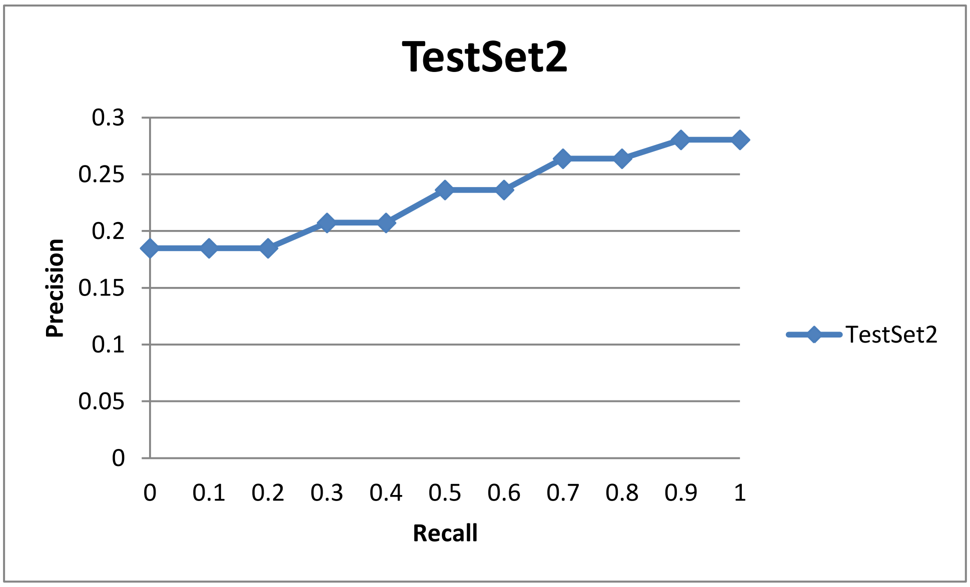


Figure 80. Precision and Recall Diagram of Test Set 2 of CPF Level 9.

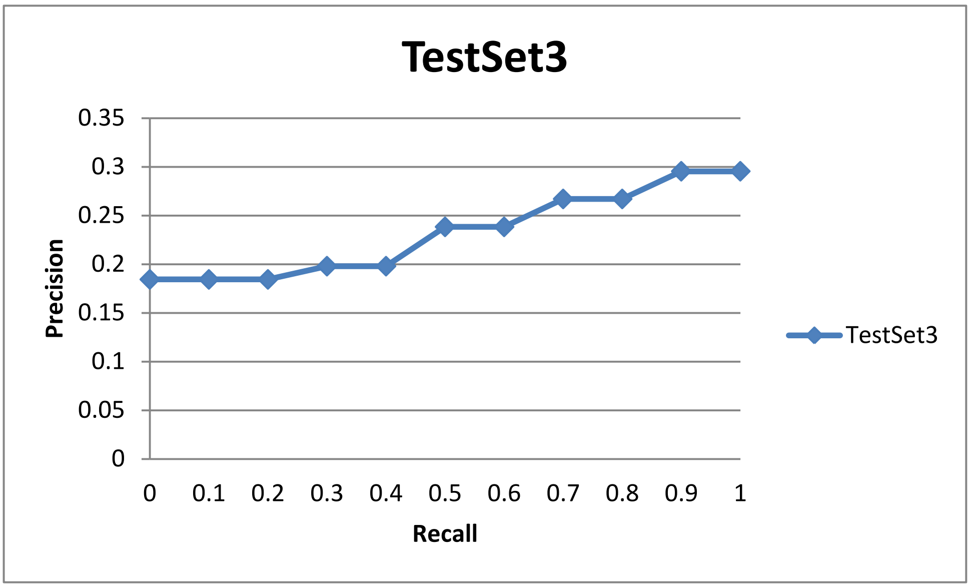


Figure 81. Precision and Recall Diagram of Test Set 3 of CPF Level 9.

Figure 82. Precision and Recall Diagram of Test Set Comparison of CPF Level 9.

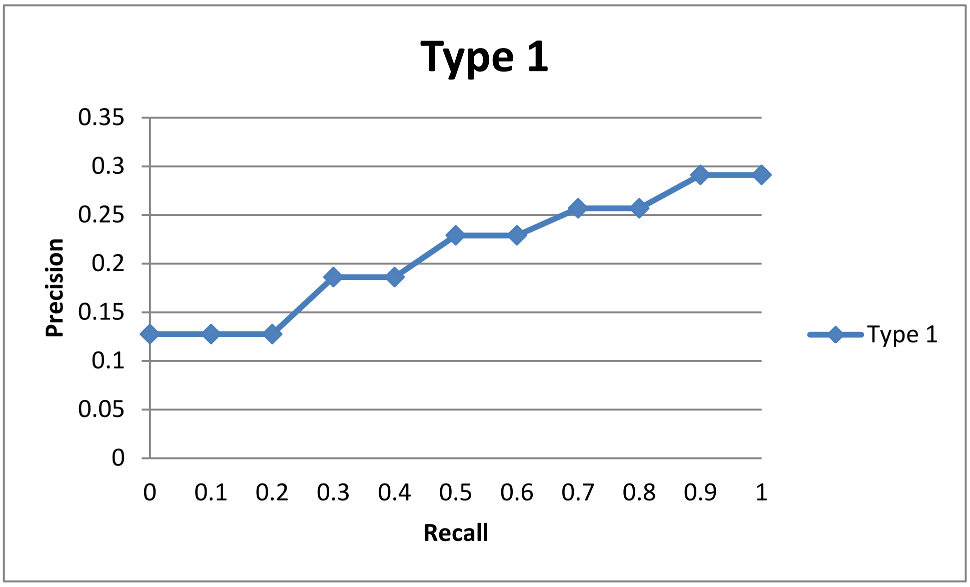


Figure 83. Precision and Recall Diagram of Type 1 of CPF Level 9.

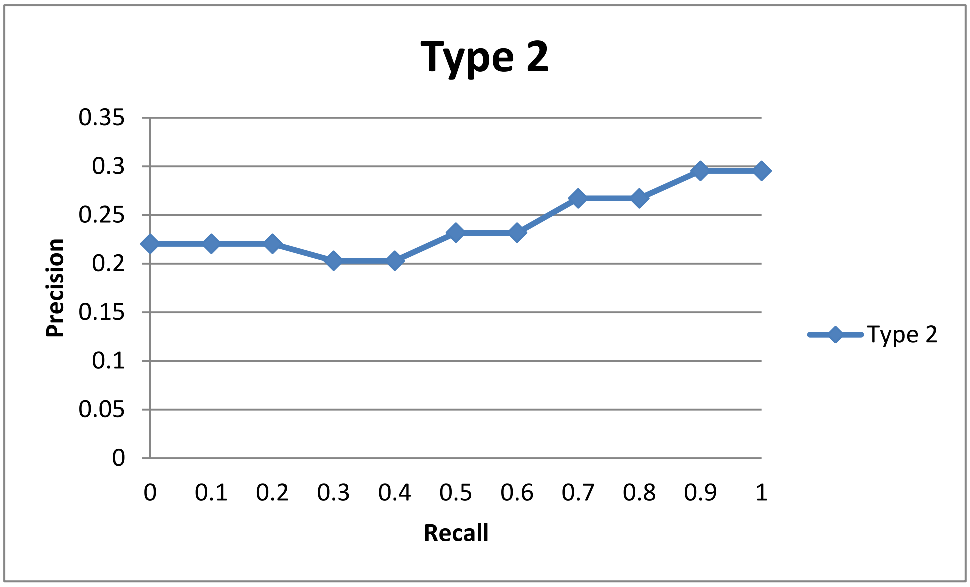


Figure 84. Precision and Recall Diagram of Type 2 of CPF Level 9.

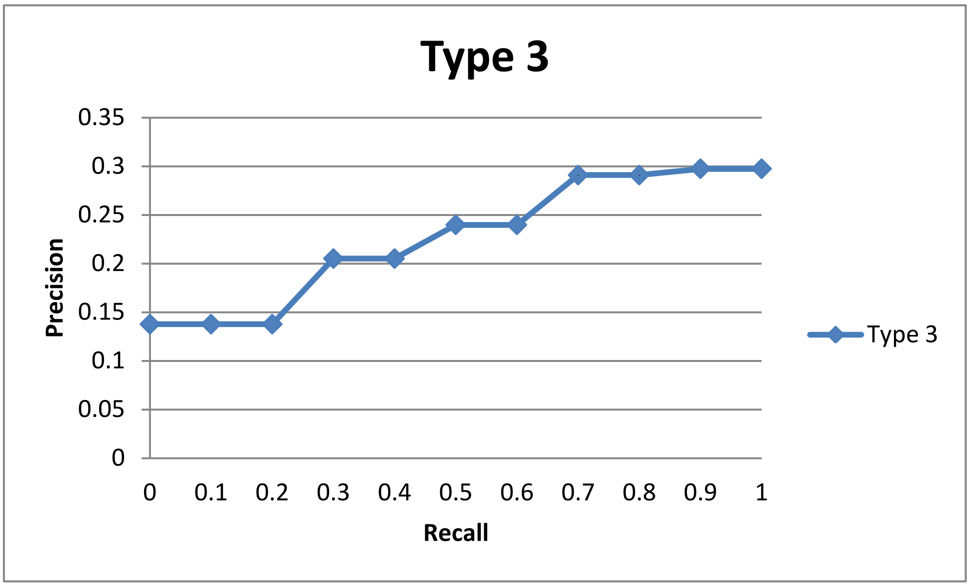


Figure 85. Precision and Recall Diagram of Type 3 of CPF Level 9.

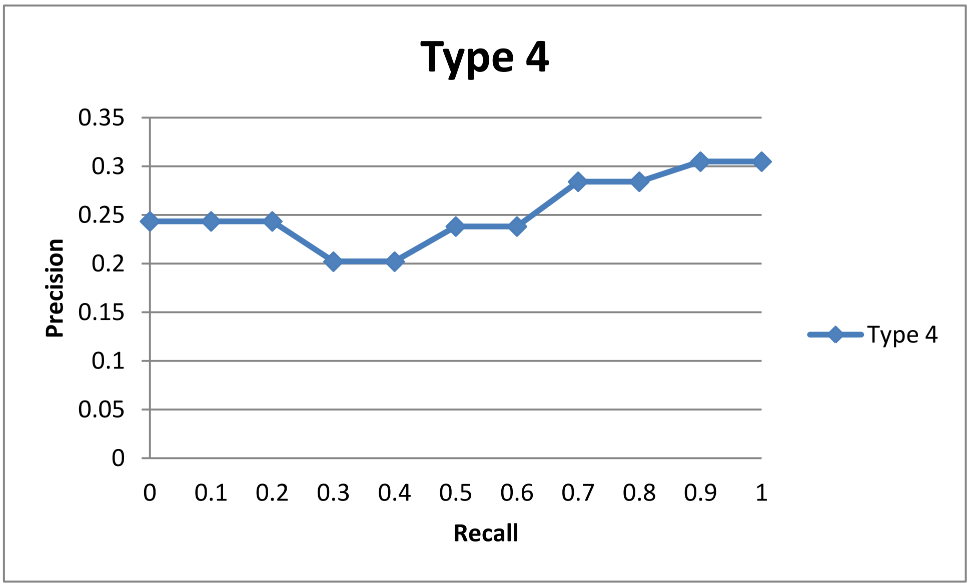


Figure 86. Precision and Recall Diagram of Type 4 of CPF Level 9.

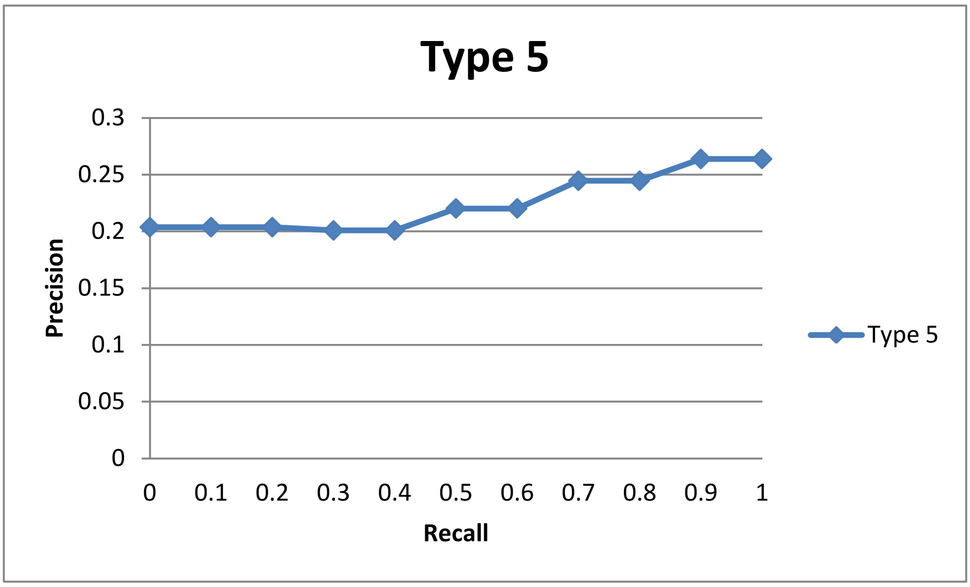


Figure 87. Precision and Recall Diagram of Type 5 of CPF Level 9.

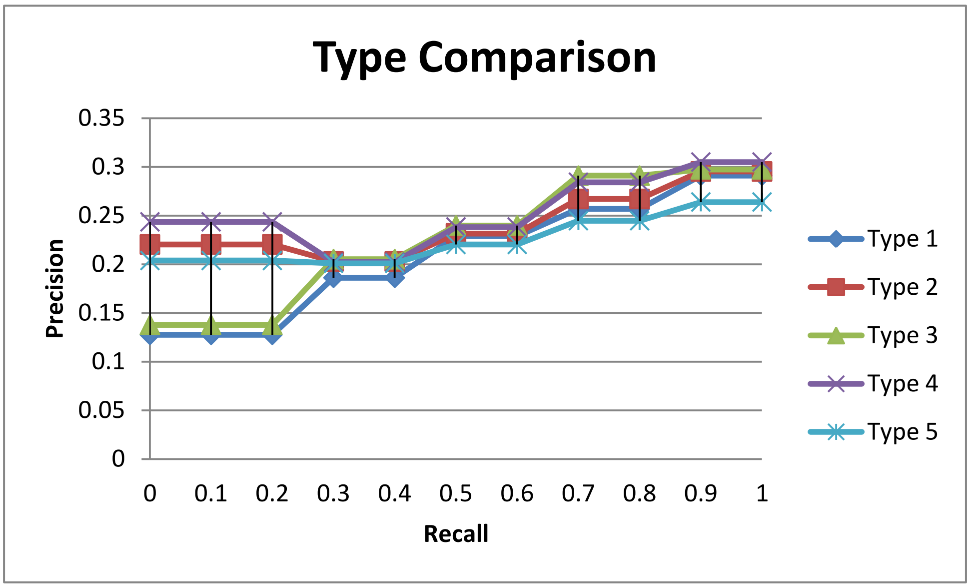


Figure 88. Precision and Recall Diagram of Type Comparison of CPF Level 9.

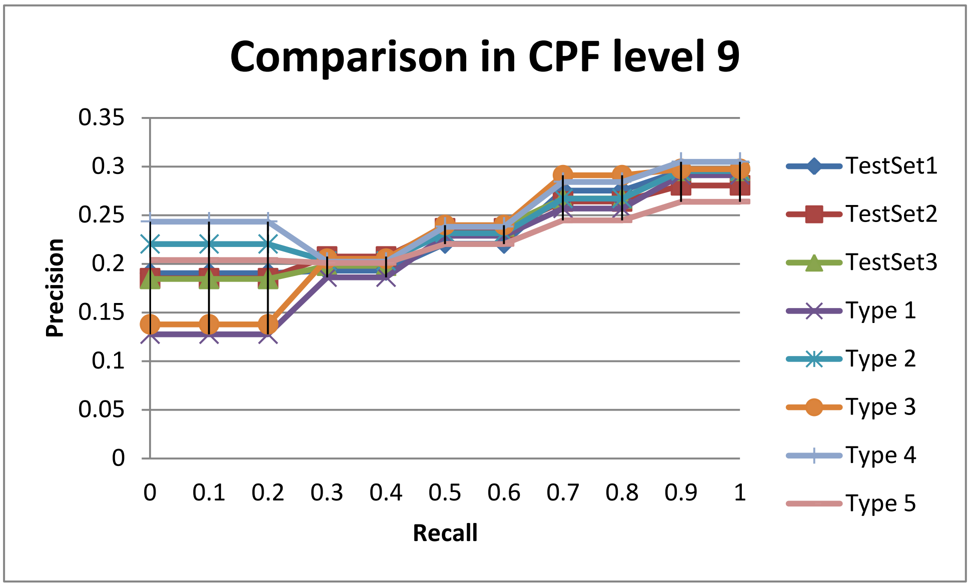


Figure 89. Precision and Recall Diagram of Comparison CPF Level 9.

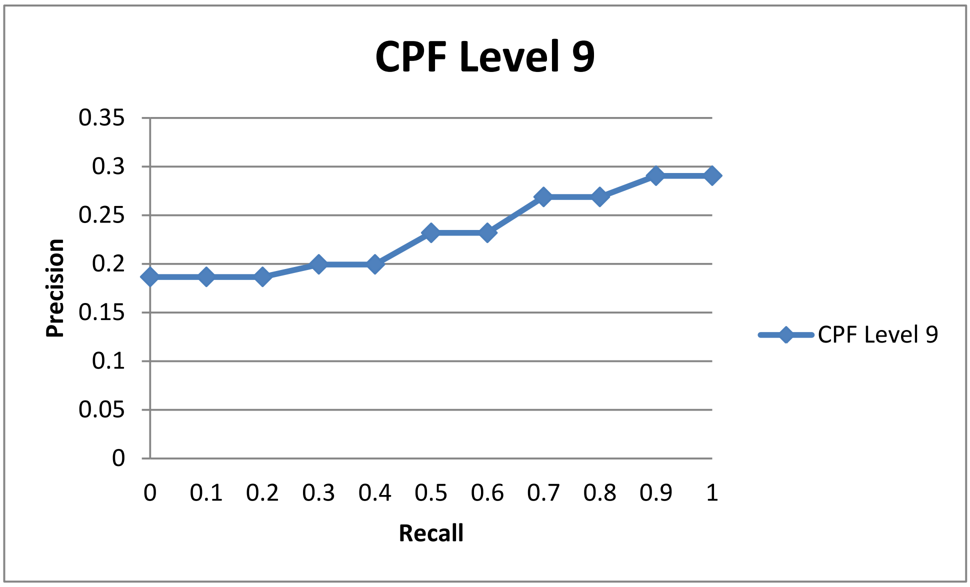


Figure 90. Precision and Recall Diagram of CPF Level 9.

Comparison of 4 Methodologies

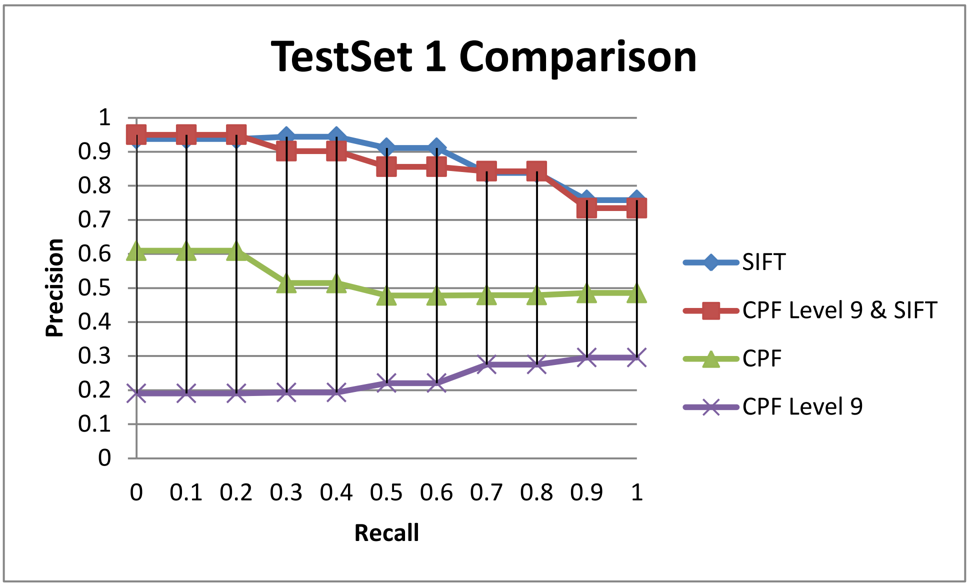


Figure 91. Precision and Recall Diagram of Test Set 1 Comparison.

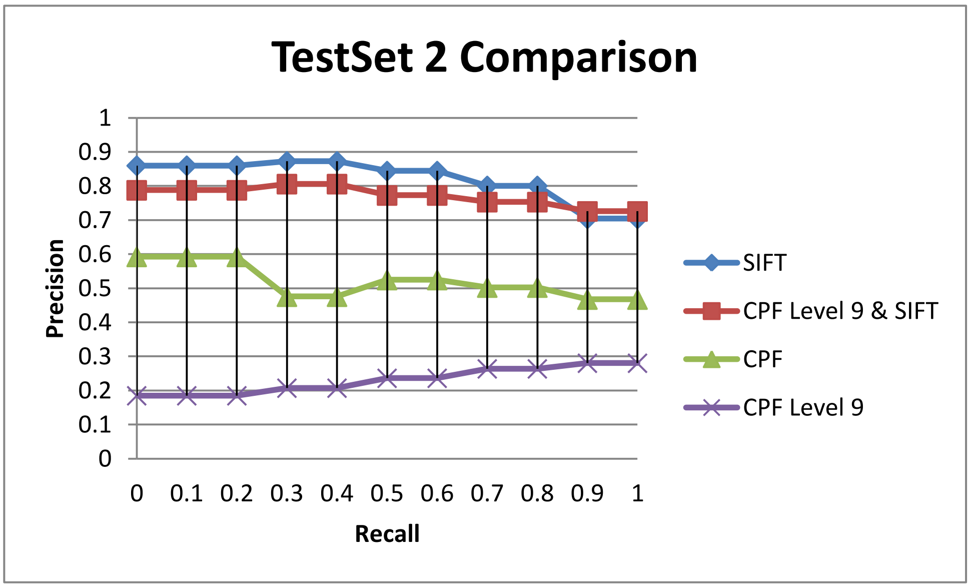


Figure 92. Precision and Recall Diagram of Test Set 2 Comparison.

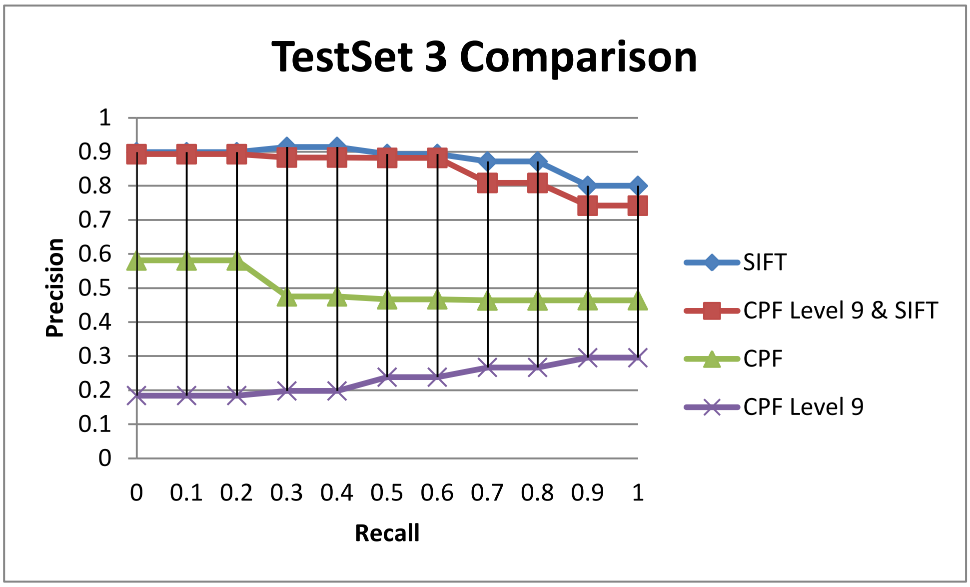


Figure 93. Precision and Recall Diagram of Test Set 3 Comparison.

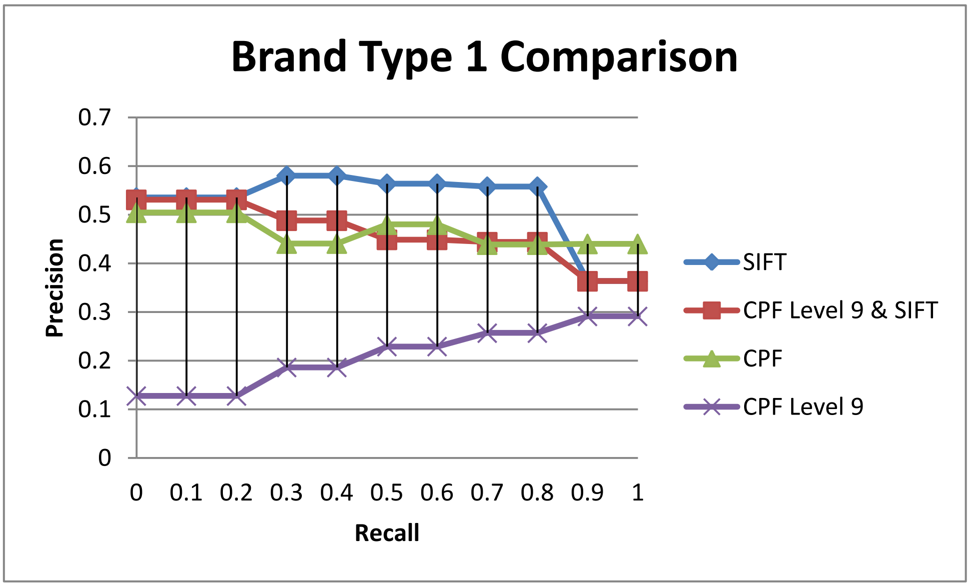


Figure 94. Precision and Recall Diagram of Brand Type 1 Comparison.

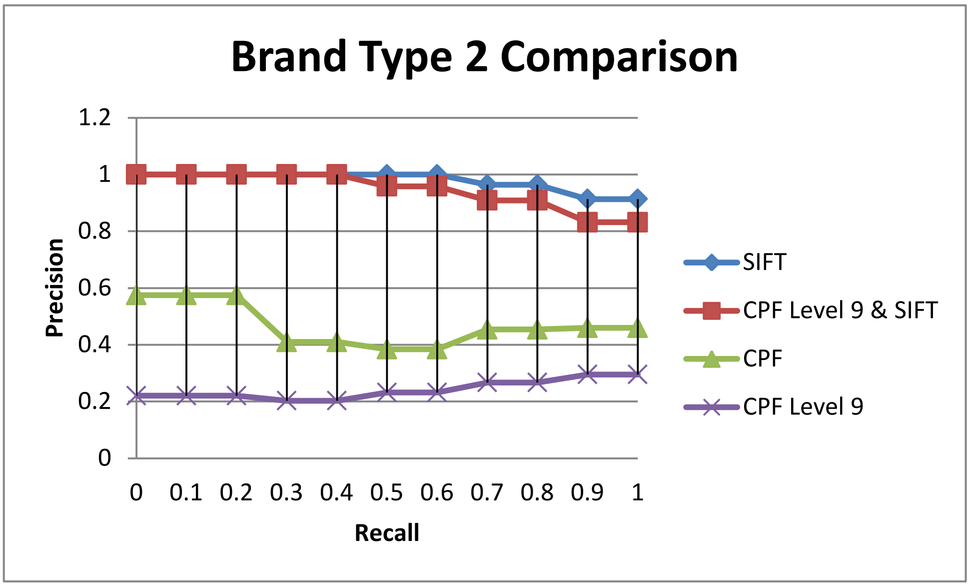


Figure 95. Precision and Recall Diagram of Brand Type 2 Comparison.

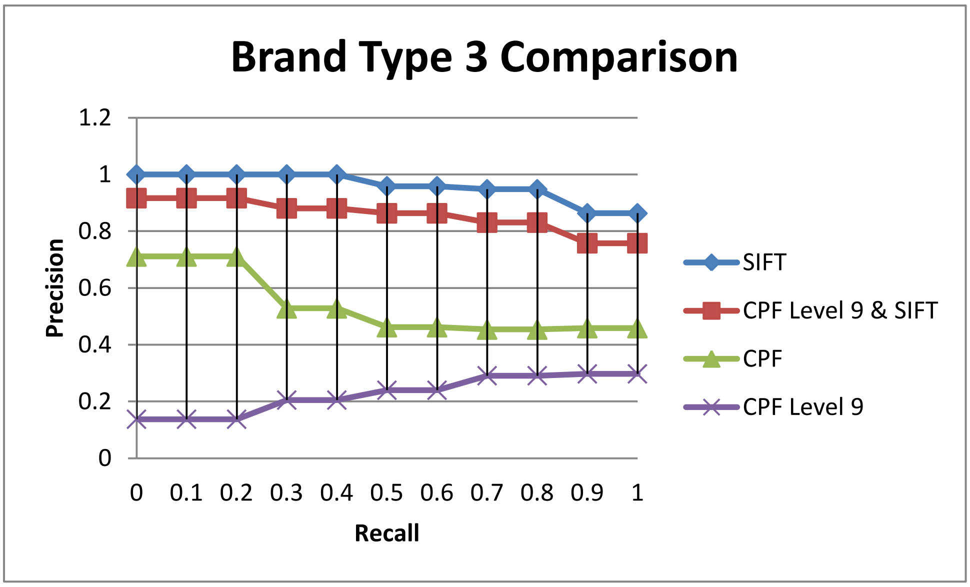


Figure 96. Precision and Recall Diagram of Brand Type 3 Comparison.

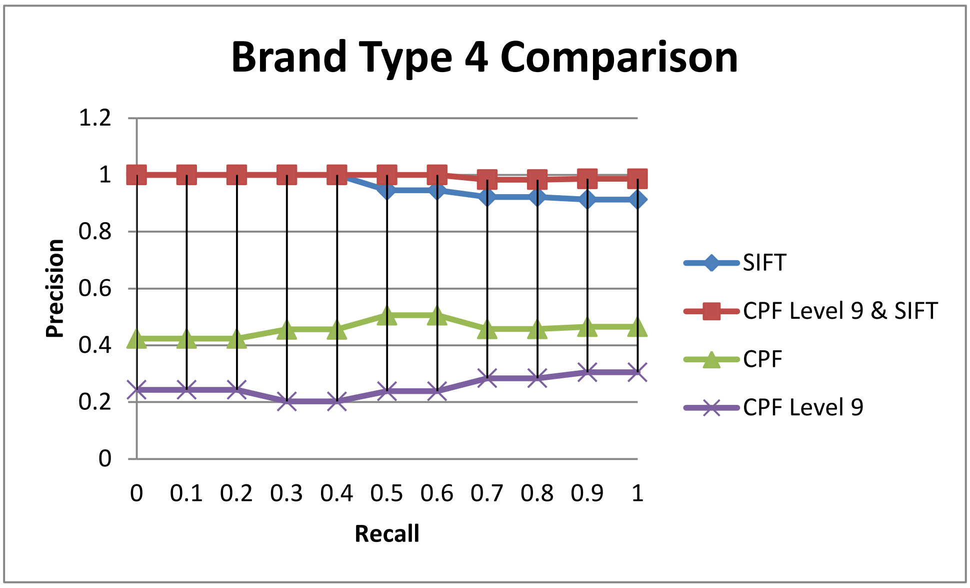


Figure 97. Precision and Recall Diagram of Brand Type 4 Comparison.

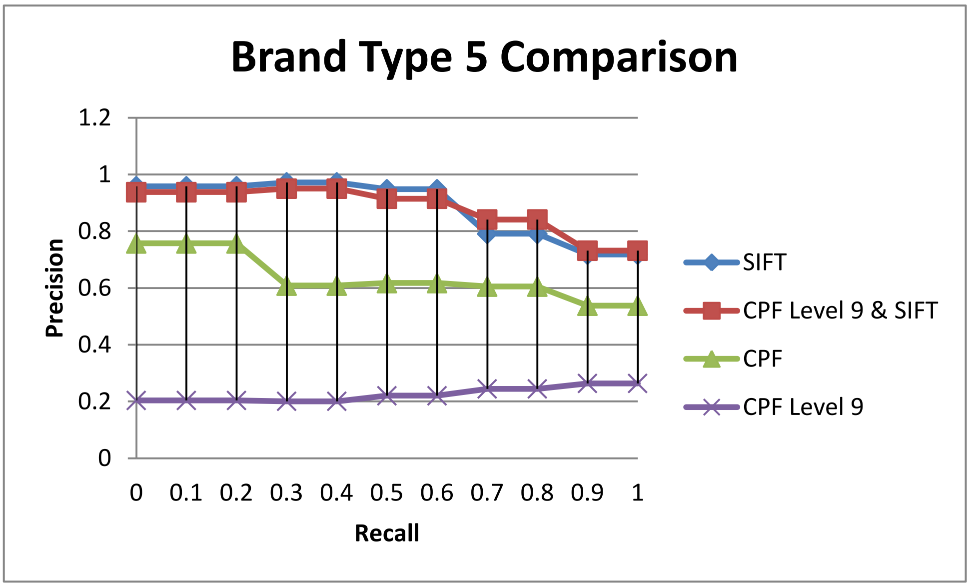


Figure 98. Precision and Recall Diagram of Brand Type 5 Comparison.

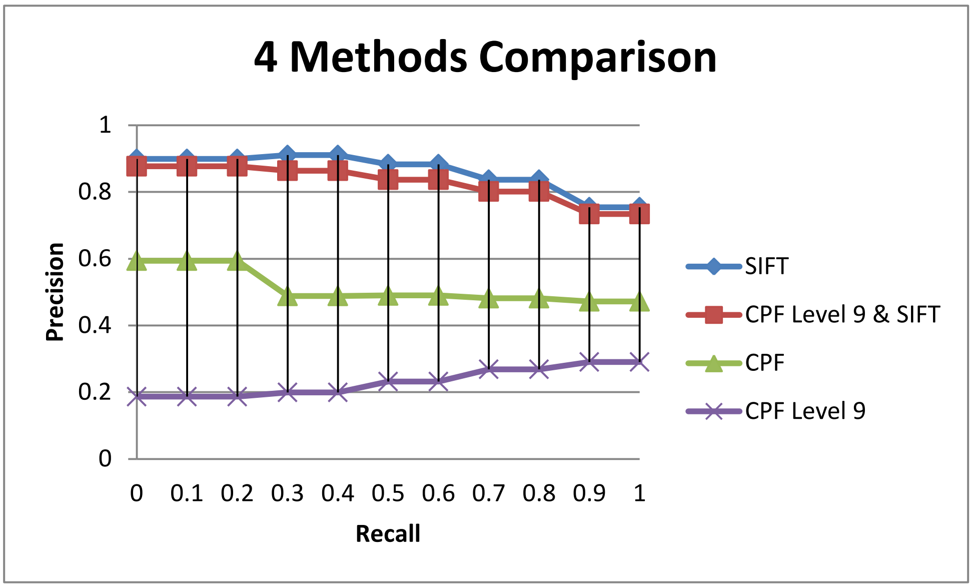


Figure 99. Precision and Recall Diagram of Comparison of 4 Methodologies.

Biography

Jennisa Areeyapinan was born on 6th September, 1988. Jennisa graduated primary education from Anuban Nakhonsawan School, graduated secondary education from Nakhonsawan School, graduated upper secondary education from Mahidol Wittayanusorn School, graduated a Bachelor of Engineering (B.Eng.) in Computer Engineering from the Faculty of Engineering, Chulalongkorn University in 2012, and entered the Master of Engineering curriculum at the Department of Computer Engineering, Faculty of Engineering, Chulalongkorn University in 2012.